Investor Sentiment: Does it augment the performance of asset pricing models?

Deven Bathia
Queen Mary University of London*

Don Bredin
University College Dublin†

Abstract

This paper examines whether incorporating various investor sentiment measures in conditional asset pricing models can help to capture the impact of size, value, liquidity, and momentum effects on risk-adjusted returns of U.S. individual stocks. Using monthly data for the period January 1980 to December 2014, we determine the significance of equity fund flow, initial public offering (IPO) first day returns, IPO volume, closed-end fund discount, equity put-call ratio, dividend premium, change in margin debt, and sentiment index, by including them as conditioning information in asset pricing models. Our results show that sentiment augmented asset pricing models significantly capture the impacts of size, value, liquidity, and momentum effects on risk-adjusted returns. In particular, we observe that conditioning beta on equity fund flow, IPO first day return, and put-call ratio capture the predictive power of equity characteristics for all the asset pricing models.

Keywords: Investor sentiment, Asset pricing, Anomalies
JEL Classification: G02, G12, G14

*E-mail: d.bathia@qmul.ac.uk

†E-mail: don.bredin@ucd.ie **Corresponding author:** Deven Bathia, School of Business and Management, Queen Mary University of London, London E1 4NS, U.K. We would like to thank two anonymous referee for providing helpful comments.

1 Introduction

The capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) assumes that a stocks beta remains constant over time. However, it may be difficult to rely on this implausible assumption, as a stock's beta continuously changes over a period of time because of the dynamic nature of the economy, as well as the nature of information available to investors. Furthermore, the CAPM argues that securities' systematic risk alone can explain its expected returns. However, Fama and French (1992) note the inability of the CAPM to explain the cross-section of average returns, their results indicating a 'flat' relationship between market beta and average returns. Previous studies have shown that firm specific characteristics also play a significant role in explaining expected stock returns. Some of these factors include firm size (Banz, 1981; Chan and Chen, 1988); earnings yield (Ball, 1978; Basu, 1977); book-to-market ratio (Fama and French, 1992; Rosenberg et al., 1985); dividend yield (Litzenberger and Ramaswamy, 1979); and leverage (Bhandari, 1988). Empirical evidence suggests that time-varying beta versions of multi-factor models can significantly capture the impact of firm pricing anomalies. For instance, Ferson et al. (1987) test the asset pricing model, where they allow expected risk premium and market betas to vary over time, noting conditional models outperform unconditional models in capturing the dynamics of factor loadings. Avramov and Chordia (2006) show that the time-varying beta version of the Fama-French three-factor model captures both size and value effects. Several other studies have found evidence supporting conditional asset pricing (e.g., Li, 2007).

Mispricing has been attributed to a number of reasons. For instance, the presence of investor under-reaction and overreaction is cited (Barberis et al., 1998; De Bondt and Thaler, 1985, 1987). The 'noise-trader' model of Black (1986) and De Long et al. (1990) suggest that security mispricing occurs when investors trade on 'noise' instead of fundamentals. The significance of investor sentiment in affecting security prices has also been also highlighted. For instance, Baker and Wurgler (2006) show that a wave of sentiment has a larger effect on securities whose valuations are highly subjective and difficult to arbitrage. By constructing sentiment indices for six major stock markets and global markets as a whole, Baker et al. (2012) find that both global and local sentiment are contrarian predictors of the time-series of cross-sectional returns within markets. Stambaugh et al. (2012) explore the role of investor sentiment in a broad set of anomalies for a cross-section of stock returns and observe that sentiment predictive power is concentrated during the period of high sentiment. Antoniou et al. (2016) find that when sentiment is high, noise traders are relatively more bullish and active for high beta stocks.

Since investor sentiment plays a significant role in affecting security prices, as evident from the above studies, we determine its significance in the conditional asset pricing framework. Specifically, we incorporate a comprehensive range of sentiment measures, as conditioning information, in different asset pricing models and determine whether they effectively capture the impact of size, value, liquidity, and momentum effects on risk-adjusted returns of individual stocks. The asset pricing models included in our study are: CAPM; the Fama-French (1993) three-factor model (FF); the FF model augmented with Pastor and Stambaugh (2003) liquidity factor (FFL); the FF model augmented with momentum factor, as explained by winners-minus-losers portfolio (FFM); and the FF model augmented with liquidity factor and momentum factor (FFLM).

In determining the significance of investor sentiment in asset pricing models, we adopt the two-pass regression framework of Avramov and Chrodia (2006). In the first pass, we run time-series regressions of excess returns of individual stocks on the risk factors of asset pricing models. In doing so, we allow factor loadings to vary with conditioning variables. Besides different sentiment proxies, the other conditioning variables we include in specifying time-varying betas are firm-level variables, represented by market capitalization and book-to-market ratio (e.g., Lewellen, 1999), and macro-economic variables, represented by default spread (Ferson and Harvey, 1999; Lettau and Ludvigson, 2001). In the second-pass regression, we run cross-sectional regression (CSR) of risk-adjusted returns from the first-pass regression, on the factors representing asset pricing anomalies. The risk-adjusted return from the first-pass regression is the sum of intercept and residuals. The variables representing asset pricing anomalies are firm size, measured by market capitalization; firm value, measured by book-to-market ratio; liquidity, measured by turnover; and momentum, measured by cumulative prior returns.

Ho and Hung (2009) determine the significance of survey-based sentiment measure in conditional asset pricing models.[1] As a proxy for survey sentiment measure, they include the University of Michigan consumer confidence index (UMCC), the individual investor sentiment index of the American Association of individual investors (AAII), and the institutional investor sentiment index of the Intelligence Investors (II). The predictive ability of survey-based sentiment measure on future stock returns has been explored by many studies. These studies have shown positive (negative) association between consumer confidence index, measured by the UMCC index and concurrent (future) stock returns (Schmeling, 2009). However, several studies have cast doubt on the predictive ability of survey-based sentiment proxies. For instance, Fisher and Statman (2000) find that the II sentiment index does not have any significant effect on future Standard and Poor 500 index returns. Furthermore, Ho and Hung (2009) do not consider removing business cycle variation from

[1] The survey sentiment measures are referred to as *direct* measure of investor sentiment as they are readily observable and directly derived from the responses to consumer survey questionnaire.

each of the three survey-based sentiment proxies, suggesting their sentiment index may not represent the cleanest measure of investor sentiment. Given the mixed findings of survey-based sentiment measures in previous studies and the concern over Ho and Hung's (2009) sentiment index, we determine the significance of various indirect sentiment measures.

Our paper contributes to the existing literature in the following areas. First, we include a comprehensive range of *indirect* (market-based) sentiment proxies in the conditional version of the asset pricing framework. As a measure of investor sentiment, we include various market-based sentiment proxies that reflect investor optimism or pessimism, including equity fund flow (EFF), IPO first day returns (IPOR), IPO volume (IPOV), closed-end fund discount (CEFD), put-call ratio (PCR), dividend premium (DP), change in margin debt (MD), and sentiment index (IND), constructed from the above seven proxies using principal component analysis (PCA). Previous studies have assessed the significance of various indirect sentiment measures and its relationship with stock returns and have found that positive sentiment generally results in concurrent positive returns and subsequent negative returns (Baker and Wurgler, 2006; Bathia and Bredin, 2013). Second, we attempt to determine the significance of each of the indirect sentiment measures by including them as conditioning information in different asset pricing models. As noted earlier, only Ho and Hung (2009) have determined the significance of the investor survey, a direct measure of sentiment, in capturing the impacts of firm pricing anomalies. However, with the survey-based (*direct*) measure, they observed that their conditional CAPM fails to capture the size effect. Since our study includes a range of *indirect* sentiment measures that have often been viewed more reliable than direct sentiment measures, our findings will highlight the significance of each of these indirect sentiment measures in capturing the impacts of the size, value, liquidity, and momentum effects. Third, since our study incorporates various market-based sentiment proxies, including some controversial ones (e.g., closed-end fund discount, and EFF), our findings will shed light on the impacts of *indirect* measure of sentiment on the dynamics of risk factor sensitivities.[2] Finally, our study provides a platform to compare the significance and performance of various market-based sentiment proxies in improving the performance of asset pricing models.

Our findings show that the sentiment augmented asset pricing models successfully capture the impacts of firm pricing anomalies. Unlike previous studies that have shown that conditional models fail to capture the impact of liquidity and momentum effects (Avaramov and Chordia, 2006), our findings suggest that the sentiment augmented asset pricing models successfully capture the impact of both these anomalies in addition to size and value effects. Overall, the evidence suggests that the role of sentiment in improving the performance of

[2]Lee et al. (1991) find CEFD is a measure of small investor sentiment, which has been subsequently challenged by several studies (Chen et al., 1993).

asset pricing models should no longer be ignored.

The remaining paper is structured as follows. In section 2, we discuss the relevant literature, followed by a discussion of the methodology in section 3. We provide a description of data in section 4. Section 5 discusses the empirical results, followed by section 6, the conclusion.

2 Literature Review

2.1 Asset Pricing

The CAPM argues that securities' systematic risk alone can explain its expected returns. However, Fama and French (1992) find a 'flat' relationship between market beta and average returns, therefore suggesting an inability of the static CAPM to explain the cross-section of average returns. Besides the systematic risk factor, previous studies have also shown that firm-specific variables play a significant role in explaining average stock returns. Some of these factors include firm size, book-to-market ratio, earnings yield, dividend yield, leverage, etc., to name a few.[3] Fama and French (1993), in their three-factor model, show that firm size (market capitalization) and firm value (book-to-market ratio) play a significant role in capturing cross-sectional variation in average stock returns. Furthermore, Fama and French (1996) highlight the significance of multi-factor models in explaining the returns of portfolios formed on earnings/price, cash flow/price and sales growth. However, the CAPM and Fama and French (1993) three-factor model failed to explain asset pricing anomalies associated with the momentum effect, as shown by Jegadeesh and Titman (1993, 2001), and Grundy and Martin (2001). More recently, Fama and French (2015) show that a five-factor model directed at capturing size, value, profitability and investment patterns in average stock returns performs better than the Fama and French (1993) three-factor model.

The failure of static CAPM in accounting for risk dynamics across individual stocks led academics to consider conditional asset pricing models in explaining firm pricing anomalies. In these models, factor loadings are allowed to vary over time. In specifying time-varying betas, previous studies have considered firm specific variables, for example, book-to-market ratio, dividend yield, market capitalization, etc (Lewellen, 1999), and variables related to business cycle conditions, for example, default spread, consumption-wealth ratio (e.g., Lettau and Ludvigson, 2001).

Jagannathan and Wang (1996) studied the ability of the conditional CAPM in explaining

[3]See Basu (1977), Banz (1981), Rosenberg (1985), Bhandari (1988), and Litzenberg and Ramaswamy (1979) for detailed discussion and significance of these variables in explaining the average stock returns.

the cross-sectional variation in average returns of stock portfolios and found that conditional models perform substantially better than the static. Furthermore, Avramov and Chordia (2006) examine the empirical performance of conditional CAPM where they allow factor loadings to vary with the conditioning information. They apply the conditional framework to single securities rather than to large numbers of stock portfolios. They observe that the time-varying betas efficiently capture size and value effects.[4] However, some studies argue that time variation in the premia is important, while time variation in factor loadings is not (Ferson and Harvey, 1991). Furthermore, Lewellen and Nagel (2006) provide a negative assessment of conditional asset pricing models. To date, there is no clear consensus on whether incorporating time variation in asset pricing models is the most appropriate.

In our assessment of sentiment augmented asset pricing models, we consider a conditional framework, wherein we scale factor loadings with firm specific variables (size and book-to-market ratio) and macro-economic variables (default spread), besides investor sentiment. The different conditional specifications considered in our analysis are discussed in the methodology section.

2.2 Investor Sentiment

Previous studies have identified several measures that reflect investor sentiment and are widely accepted as '*sentiment*' measures by practitioners (e.g., EFF, percentage change in MD). In our conditional asset pricing framework, we study the significance of sentiment proxies in capturing the impacts of the size, value, liquidity, and momentum effects on risk-adjusted returns of individual stocks.

We include EFF as a measure of investor sentiment. Previous studies have found mixed evidence for this sentiment measure, attributing the positive association between concurrent fund flow and stock returns to either a price pressure effect or an information effect (Warther, 1995). However, few studies have found evidence of price pressure effects, whereby increases in fund flow result in increases in concurrent stock returns, and price reversals in subsequent months (Bathia and Bredin, 2013).[5] Furthermore, Brown et al. (2003) show that daily mutual fund flow can be considered an instrument of investor sentiment. Frazzini and Lamont (2006) use mutual funds flows as a measure of investor sentiment and find that high sentiment predicts lower future returns, and growth stocks tend to be the main victims of high sentiment.

[4]Also see Ferson and Harvey (1999), and Wang (2003), who show that conditional models outperform unconditional models in explaining stock returns.

[5]Bathia and Bredin (2013) note the causality running from the equity fund flow to returns for value stocks and overall market is due to the price pressure effect.

As a proxy for small investor sentiment, we include closed-end fund discount (CEFD). This measure continues to remain popular, although controversial. There remains very little consensus on whether the discount on closed-end funds, the percentage difference between fund net asset value (NAV) and fund share price, can be considered as a measure of investor sentiment. As fixed numbers of shares are issued in the closed-end fund, the fund NAV should be equal to the fund share price. However, Weiss (1989) has shown that closed-end funds start trading at an average of 10% discount within 120 days of trading. Furthermore, Lee et al. (1991) show that when CEFD is high (low), investors are pessimistic (optimistic) about future returns. However, these findings were subsequently challenged by several authors (Chen et al., 1993). We determine the significance of CEFD by including it as a conditional variable in specifying time-varying beta.

Previous studies have also shown that the information contained in non-price derivative measures can be helpful in determining prevailing sentiment levels in the stock markets. Some of these measures include open interest, volatility index (VIX), and equity put-call ratio (PCR). Studies by Easely et al. (1998) and Pan and Poteshman (2006) show that information contained in option volume is useful in determining future stock prices.

Numerous trading indicators are often considered to reflect sentiment levels of investors. Some of these measures include trading volume, percentage change in short interest and percentage change in MD, etc. and have been included in previous studies to determine the effect on stock returns (Brown and Cliff, 2004). In our study, we include the percentage change in margin debt (MD). The increase in MD is often considered a bullish indicator since investors rely heavily on MD when they perceive excessive optimism about the future economy. Baker and Wurgler (2006) consider 'dividend premium' (DP) as a measure of sentiment, as it helps to assess the relative demand of investors for dividend paying stocks.[6] Similarly, IPO first day returns (IPOR) are associated with investor enthusiasm, as previous studies have shown that IPO are mostly under-priced (Ljungqvist, 2006). Similarly, IPO volume (IPOV) is often considered a measure of sentiment. Previous studies have shown that IPO activity usually happens during boom times or when investor sentiment is high.[7]

In our sentiment augmented conditional asset pricing study, we include all the above measures in isolation and also construct a sentiment index based on their first principal component.

[6] Baker and Wurgler (2004) define 'dividend premium' as the difference between the average market-to-book ratio of dividend payers and non-payers. They show that dividend non-payers tend to pay dividends when demand from investors is high and tend to avoid paying dividend when demand is low.

[7] Also see Ritter (1991), and Ibbotson and Ritter (1995) for detailed discussion of the IPO and relevant literature.

3 Methodology

In assessing the significance of different sentiment measures in explaining asset pricing anomalies, we extend the two-pass regression framework of Avramov and Chordia (2006). In the first-pass regression, we regress excess stock returns on the asset pricing factors, where we allow factor loadings to vary conditionally over time. In the second-pass regression, we run CSRs of the risk-adjusted returns, which is the sum of the pricing error and the residual from the first-pass regression, on the firm characteristics of size, book-to-market ratio, and other variables that represent liquidity (turnover) and momentum effects (cumulative prior returns). The conditional framework for testing sentiment augmented asset pricing models is explained below.

Under the conditional framework of the K-factor model, returns for security i is given by:

$$E_{t-1}(R_{it}) = R_{ft} + \Sigma_{k=1}^{K} \gamma_{kt-1} \beta_{ikt-1} \tag{1}$$

where E_{t-1} is the conditional expectations operator, R_{it} is return on stock i at time t, R_{ft} is the risk-free rate, γ_{kt-1} is the risk premium for factor K at *t-1*, and β_{ikt-1} is the conditional beta of asset i corresponding to factor K at *t-1*. Following Lewellen et al. (2008), the above pricing specification imposes theoretical restrictions ex ante in that the zero-beta return equals the risk-free rate, and the factor premium is equal to the excess return on the factor.

Since the aim of this study is to determine whether asset pricing anomalies exert any impacts on risk-adjusted returns, our generic form of a two-pass conditional framework can be shown as:

$$R_{it}^{*} \equiv R_{it} - [R_{ft} + \beta(\theta; s_{t-1}, f_{t-1}, m_{it-1})' X_t] \tag{2}$$

$$R_{it}^{*} = \alpha_{0t} + \beta_t^{*} Y_{it-1} + e_{it} \tag{3}$$

where R_{it}^{*} is the estimated risk-adjusted return of stock i at time t and is the sum of pricing errors (intercept) and residual, both obtained from the first-pass regression as per different specifications explained later in this section. θ represents the parameters that capture the dependence of β on investor sentiment, s_{t-1}, firm specific characteristics (size and B/M ratio), f_{it-1}, and macro-economic variable (default spread), m_{t-1}. X_t represents vector of risk factors specified in the asset pricing model. Y_{it-1} includes all the factors that represent size, value, liquidity, and momentum effects. Since the null hypothesis of exact pricing should successfully capture asset pricing anomalies in the first-pass time-series regression, we expect to find the factor loadings, represented by β_t^{*} in equation 3, to be statistically no different from zero. In specifying firm characteristics variables, we use lagged value at one period *t-1* to account for bid-ask effects and thin trading because of possible biases of the risk-adjusted returns.

Now, the conditional beta equation is given by:

$$\beta_{i,t-1} = f(z_{t-1}) \tag{4}$$

$$\beta_{i,t-1} = \beta_{i,0} + \beta_{i,1}(z_{t-1}) \tag{5}$$

where $\beta_{i,t-1}$ is the conditional beta to be modelled, and $f(z_{t-1})$ is the function of all 'z' exogenous variables at *t-1*. In our conditional asset pricing framework, we condition beta as a function of sentiment measure (s_{t-1}), macro-economic variable (default spread, (m_{t-1})), and firm characteristics (($size_{t-1}$) and (B/M_{t-1})). The conditional beta can then be expressed in the following form:

$$\begin{aligned}\beta_{i,t-1} = \quad & \beta_{i,0} + \beta_{i,1}s_{t-1} + \beta_{i,2}m_{t-1} + \beta_{i,3}(m_{t-1})(s_{t-1}) \\ & +(\beta_{i,4} + \beta_{i,5}s_{t-1} + \beta_{i,6}m_{t-1})size_{i,t-1} \\ & +(\beta_{i,7} + \beta_{i,8}s_{t-1} + \beta_{i,9}m_{t-1})B/M_{i,t-1}\end{aligned} \tag{6}$$

We model the beta (β) in the first-pass regression in four different ways, utilizing the specification below:

Specification A: function of (size + B/M) and s [i.e. $\beta_{i,2} = \beta_{i,3} = \beta_{i,6} = \beta_{i,9} = 0$]
Specification B: function of m and s [i.e. $\beta_{i,4} = \beta_{i,5} = \beta_{i,6} = \beta_{i,7} = \beta_{i,8} = \beta_{i,9} = 0$]
Specification C: function of s [i.e. $\beta_{i,2} = \beta_{i,3} = \beta_{i,4} = \beta_{i,5} = \beta_{i,6} = \beta_{i,7} = \beta_{i,8} = \beta_{i,9} = 0$]
Specification D: function of all variables; s, m, size and B/M [i.e. all $\beta \neq 0$]

We also test the unconditional case for each model, where we do not incorporate sentiment measures, firm characteristics (size and B/M), and macro-economic variable. We illustrate first-pass regression using conditional beta for a single factor CAPM. For instance, the first-pass regression of Specification D of the CAPM will be given by,

$$\begin{aligned}R_{it} - R_{ft} = \alpha_i + \gamma_t[\beta_{i,0} + \beta_{i,1}(s_{t-1}) + \beta_{i,2}(m_{t-1}) + \beta_{i,3}(s_{t-1})(m_{t-1}) \\ +(\beta_{i,4} + \beta_{i,5}(s_{t-1}) + \beta_{i,6}(m_{t-1}))size_{i,t-1} \\ +(\beta_{i,7} + \beta_{i,8}(s_{t-1}) + \beta_{i,9}(m_{t-1}))B/M_{i,t-1}] + \epsilon_{i,t}\end{aligned} \tag{7}$$

We implement the Fama-Macbeth (1973) approach in estimating the precision of CSR estimates. To account for error-in-variable bias as a result of Fama-Macbeth CSR, we implement the corrections proposed by Shanken (1992).[8]

[8] Following the recommendations from an anonymous referee, we also report t-values using Jagannathan and Wang (1998) (JW) standard error corrections. The results are consistent irrespective of whether the Shanken (1992) or Jagannathan and Wang (1998) standard error corrections are adopted.

4 Data

4.1 Market Data

The main dataset consists of monthly equity data for all the equity shares listed on the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX). The data are sourced from the Center for Research for Security Prices (CRSP) and the COMPUSTAT database. In our analysis, we only consider common shares (CRSP share code 10 and 11) for the period January 1980 through December 2014. Given the lack of sentiment data pre-1980 and the significant survivorship bias in pre-1980 COMPUSTAT data, our sample starts from 1980.[9] This gives us approximately 420 monthly observations. The common stock should satisfy the following criteria to be included in our analysis. First, the returns data for the current month t and previous 36 months should be available from the CRSP. Second, sufficient data on stock price and common shares outstanding should be available to compute size, which is measured by market capitalization. Third, sufficient data on *t-2* trading volume should be available to compute turnover (T/O). Fourth, sufficient data should be available from COMPUSTAT for computing book-to-market (B/M) ratio as of December of the previous calendar year. Following Fama and French (1992), the value of B/M for July of year t to June of year *t+1* is computed using accounting data at the end of calendar year *t-1*. The B/M ratio greater than 0.995 fractile or less than 0.005 fractile is set as 0.995 and 0.005, respectively. We drop all the firms that have negative B/M ratio.

After this screening process, we arrive at a total of 3,567 common stocks. In running CSRs, we consider natural logarithmic transformation of all our monthly variables (except turnover and cumulative past return). For instance, size, measured by market capitalization (in billions of dollars), is the natural logarithm of the market capitalization of an individual firm. Similarly, B/M is the logarithmic transformation of the book-to-market ratio. Turnover, a measure of liquidity, is determined by dividing trading volume by the number of shares outstanding. To proxy for momentum, we calculate Ret 2-3, Ret 4-6 and Ret 7-12, which are the cumulative returns over the past second to third months, past fourth to sixth month and past seventh to twelfth months, respectively. As a proxy for market returns, we consider CRSP value-weighted returns, including distributions and one-month T-Bill rate, as a proxy for risk-free rate. The Fama-French factors, small-minus-big (SMB) and high-minus-low (HML), and momentum factor are sourced from the Kenneth French

[9] It is widely acknowledged that survivorship-bias exists in COMPUSTAT's pre-1978 data. For example, Davis (1994) notes the 1963-1978 period to be a period where COMPUSTAT data are more susceptible to survivorship bias. Also see Kothari et al. (1995), who provide a detailed assessment of COMPUSTAT selection procedure.

data library.[10] The proxy of Pastor and Stambaugh's non-traded liquidity factor, which is the difference between value-weighted average return on stocks with high sensitivities to liquidity less the value-weighted average return on stocks with low sensitivities to liquidity, is sourced from Lubos Pastor's research homepage.[11] We include the default spread as a proxy for macro-economic variable. Default spread is measured by taking the differences in yield between Moody's BAA and AAA corporate bonds (data taken from the Board of Governors of the Federal Reserve System).

Table 1 reports the summary statistics of time-series averages of cross-sectional means and standard deviation for 3,567 NYSE-AMEX stocks for the period January 1980 to December 2014. The fourth and fifth column labelled coefficients and t-values are Fama Macbeth coefficients and t-values derived from running cross-sectional OLS regression of excess returns on the firm specific variables (size and B/M), turnover, and cumulative prior returns. The negative and statistically significant coefficient for size, and positive and statistically significant coefficient of B/M ratio indicate that small firms and firms that have high B/M ratio earn higher excess returns. This finding is consistent with the previous studies (e.g., Avramov and Chordia, 2006). We find statistically significant negative coefficients for turnover, further indicating that firms with lower liquidity earn higher excess returns. Furthermore, we obtain positive and significant coefficient estimates for cumulative prior returns, suggesting that prior returns are positive related to excess returns; the finding which is consistent with the momentum phenomenon highlighted by Jegadeesh and Titman (1993).

4.2 Investor Sentiment Data

In our sentiment augmented asset pricing model study, we obtain the market-based sentiment proxy from several sources. The equity fund flow (EFF) data is obtained from the Investment Company Institute. Following Indro (2004), we compute EFF as a percentage of total equity fund assets. We source margin debt (MD) data from the NYSE Factbook and the equity options volume data from the Chicago Board of Options Exchange. Following Pan and Poteshman (2006), we calculate put-call ratio (PCR) as put volume divided by total equity options volume (put and call volume). IPO volume (IPOV) and IPO first day returns (IPOR) are sourced from Jay Ritter's data library, and dividend premium (DP) and closed-end fund discount (CEFD) data are sourced from Jeffery Wurgler web page.[12]

[10] Prof. French data library is available at, `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

[11] `http://faculty.chicagobooth.edu/lubos.pastor/research/`

[12] The data from Jeffery Wurgler webpage can be accessed at `http://people.stern.nyu.edu/jwurgler/` whereas data library of Prof Jay Ritter can be accessed at `http://bear.warrington.ufl.edu/ritter/`

As each individual sentiment proxy may include both sentiment and non-sentiment, idiosyncratic component, we first use PCA to isolate the sentiment component. Before constructing a sentiment index, we remove business cycle variation from each of these proxies, where we regress each raw sentiment variable on five macro-economic variables and use the residuals from the regression in the PCA. These residuals can, therefore, be considered a cleaner measure of investor sentiment.[13] The five macro-economic variables on which raw sentiment proxies are regressed are the change in consumer durables, consumer non-durables, consumer services (data obtained from the U.S. Department of Commerce, Bureau Economic Analysis), dummy variable for NBER recession, and change in industrial production (data obtained from the Board of Governors of the Federal Reserve System).

The resulting index of the orthogonalized sentiment proxies using PCA is of the following form:

$$\begin{aligned} SENT_t = 0.4399 FundFlow + 0.3332 IPOReturns + +0.4425 IPOVolume \\ +0.4002 CEFD - 0.4312 PCR - 0.3114 DivPremium + 0.2380 MarginDebt \end{aligned} \tag{8}$$

where $SENT_t$ represents the sentiment index (IND). The resulting sentiment index (IND, henceforth) is constructed after standardizing each sentiment proxies. This index, constructed from the first principal component explains 42% of the total standardized variance of the orthogonalized proxies.

5 Empirical Results

In discussing the results for each model, we will look at the significance of the Fama-Macbeth coefficient obtained from running the second-pass cross-sectional OLS regression.[14] As noted before, the null hypothesis of exact pricing should successfully capture pricing anomalies in the first-pass time-series regression. Therefore, the coefficients obtained in the second-pass cross-sectional OLS regression should be insignificant. However, should the obtained Fama-Macbeth coefficient in the second-pass cross-sectional OLS regression be significant, it indicates that the pricing anomaly variables (size, value, liquidity, and momentum) are related to the cross-section of risk adjusted returns. We also compare the magnitude of adjusted R^2 obtained in the unconditional case for all the models in our study

`ipodata.htm`.

[13] The approach that we adopt is similar to Baker and Wurgler (2006). They construct their sentiment index using six sentiment variables, viz., CEFD, IPO first day returns, IPO volume, dividend premium, NYSE share turnover, and the equity shares in new issues for the period 1961 to 2005.

[14] To account for error-in-variable bias from running the cross-sectional OLS regression, we also report Shanken (1992) corrected t-values, besides Fama-Macbeth t-values.

with the conditional case. The lower adjusted R^2 and insignificant coefficient will indicate the efficacy of the model. Furthermore, if this holds true for conditional models, then it indicates that the conditional models outperform the unconditional models in capturing the firm pricing anomalies. We discuss our findings for unconditional models and each of the five conditional models in the following subsection.

5.1 Unconditional models

The results for each of the five unconditional asset pricing models are presented in Table 2. In this table, we report the Fama-Macbeth coefficients and the respective t-values from running the cross-sectional OLS regression of the monthly risk-adjusted returns of individual stocks on the variables representing firm characteristics (size and B/M), and liquidity (turnover) and momentum (cumulative past returns: Ret 2-3, Ret 4-6 and Ret 7-12) effects.

In the case of unconditional CAPM, we find that the firms with small market capitalization, high B/M ratio, low T/O, and high prior returns provide higher risk-adjusted excess returns. Our results suggest that the unconditional CAPM fails in capturing asset pricing anomalies. In the case of the Fama-French three-factor model, we again obtain significant coefficient estimates for all pricing anomalies. Although the coefficient estimates are qualitatively similar to that of unconditional CAPM, they are relatively lower in absolute terms (e.g., in the case of book-to-market ratio, it is 0.12 as opposed to 0.14). Our findings for the three-factor model are consistent with the unconditional CAPM regarding the validity of the model. The findings, therefore, suggest the failure of the three-factor model in its ability to explain predictive power of equity characteristics. The addition of SMB and HML risk factors, in addition to excess market returns, however, result in a marginal decrease in the adjusted R^2 from 4.11% of the unconditional CAPM to 4.06% of the unconditional FF model. This indicates that the FF model is slightly relatively better than the CAPM in explaining risk adjusted returns.

Similar findings were also observed in the case of the unconditional FFL model, where we add the Pastor-Stambaugh (2003) liquidity factor. We again obtain significant coefficient estimates. These estimates are qualitatively similar relative to those of the unconditional CAPM and FF model. However, the updated estimates are more significant at least in the case of turnover and prior returns. Furthermore, the overall explanatory power, adjusted R^2, of the unconditional FFL model is nearly the same as that of three-factor model (i.e. 4.07% as opposed to 4.06%), indicating that the inclusion of liquidity factor does not contribute much in explaining the predictive power of equity characteristics.[15] We also augment the Fama-French three-factor model with the momentum factor (FFM), cumula-

[15] Also see Avramov and Chordia (2006), who observe similar findings.

tive past returns, to determine its significance in explaining asset pricing anomalies. The momentum factor represents the momentum strategy of buying winners and selling losers, as shown by Jegadeesh and Titman (1993). The findings of the unconditional FFM model is again qualitatively similar to those of the earlier models discussed above. We again obtain significant coefficient estimates; however, these are relatively smaller in absolute values than those of the other three models discussed above (i.e. CAPM, FF, and FFL). Furthermore, the adjusted R^2 of the unconditional FFM model is lower than the CAPM, FF, and FFL models (i.e. 4.04%). The lower adjusted R^2 shows that the FFM model is relatively better than the unconditional versions of the CAPM, FF, and FFL models in capturing predictive power of firm attributes. We also augment the FF model by including both liquidity and momentum factors (FFLM), the findings of which are relatively similar to those of the FFM model. Although there is a slight improvement in significance levels, coefficient estimates are relatively similar in absolute terms. Furthermore, the adjusted R^2 remains the same as that of FFM model (i.e. 4.04%). In all, it seems that adding the liquidity factor to the FFM model does not really add value in explaining cross-section of risk-adjusted returns, and it also fails to capture any of the market anomalies.

5.2 Conditional capital asset pricing model (CAPM)

The results of the conditional CAPM are reported in Table 3. All sentiment proxies, including sentiment index, are highlighted in the first column. The corresponding Fama-Macbeth coefficient estimates are determined for four anomalies (size, B/M, turnover, and prior returns) for four different specifications (A, B, C, and D), and are reported in the first row for each of the eight proxies for investor sentiment. For each coefficient estimate, we report both Fama-Macbeth t-values (fmb) and Shanken (1992) corrected t-values (shk) in the second and third rows, respectively. The adjusted R^2 for each sentiment proxy and for each specification is reported in the fourth row under size anomaly.

In our single factor conditional CAPM, we find that the size effect is effectively captured for all sentiment proxies (except PCR) when beta is scaled by investor sentiment and macroeconomic variable (spec B). Furthermore, the size anomaly is captured for all specifications when IPOR and margin debt enters the beta conditioning process as we obtain insignificant coefficient estimates. We also observe that the conditional CAPM successfully captures the value effect for all sentiment measures except for equity fund flow. For instance, by conditioning beta on default spread and PCR (spec B), the value effect is captured on risk-adjusted returns of individual stocks. When we include sentiment measures along with firm-specific characteristics and default spread (spec D) in the beta scaling process, we obtain insignificant coefficient estimates for all sentiment measures, except for EFF, CEFD and DP. Furthermore, we find that three sentiment proxies, viz., CEFD, PCR and DP, play a significant role in capturing liquidity and momentum effects on risk-adjusted returns. For instance, when the beta is scaled by firm characteristics (size and B/M), default spread, and CEFD (spec D), we obtain negative and insignificant estimates for turnover and positive and insignificant estimates for Ret 2-3 and Ret 7-12. In all, we find that only CEFD and DP play a significant role in capturing the impacts of all the market anomalies (i.e. size, value, liquidity, and momentum).

Our findings are not consistent with that of Ho and Hung (2009), who observe that sentiment augmented conditional CAPM fails to capture the impacts of the value, liquidity, and momentum effects on risk-adjusted returns of individual stocks. This difference is because they use *direct* measures of investor sentiment, investor survey, in the beta conditioning process. It therefore seems that market-based sentiment proxies do a better job in capturing pricing anomalies. Our findings are also not consistent with that of Avramov and Chrodia (2006), who find conditional CAPM fails to capture the impact of firm pricing attributes on risk-adjusted returns. We note that the difference in results is mainly because Avramov and Chordia (2006) do not include investor sentiment as conditioning information in their asset pricing framework.

As noted earlier, we also look at the adjusted R^2 to determine the model efficacy in capturing the predictive power of firm attributes. The adjusted R^2 for specification B and C of sentiment augmented conditional CAPM is often relatively lower for most of the sentiment proxies than that of unconditional CAPM (see Table 2 and 3). Although the adjusted R^2 of specification B and C is marginally lower or similar for all sentiment proxies except for IPOR and IPOV, it is significantly lower for CEFD, PCR, and dividend premium in the case of specification B (when beta is scaled by sentiment and default spread). For instance, the magnitude of the adjusted R^2 is significantly reduced from 4.11% for the unconditional CAPM (see Table 2) to 2.45% for the CEFD (see spec B, Table 3). Furthermore, when firm characteristics along with sentiment (spec A) and firm characteristics along with sentiment and default spread (spec D) enter the beta conditioning process, adjusted R^2 increases marginally for all sentiment proxies, except for PCR where we obtain marginally lower adjusted R^2 for specification (A and D). This finding might suggest that the inclusion of firm characteristics along with sentiment and default spread in the conditioning set do not add value in improving model efficiency, although it contributes to capturing market anomalies. Furthermore, the improvement in the adjusted R^2 for spec B and C suggests that the conditional models are relatively better than unconditional models in capturing the predictive power of firm attributes. In summary, we note that the inclusion of CEFD and DP along with default spread (spec B) contributes to capturing size, value, liquidity, and momentum effects on risk-adjusted returns of individual stocks.

5.3 Conditional Fama-French three factor model (FF)

The findings of the conditional FF model are reported in Table 4. Our results show that the size effect is effectively captured when each of the eight sentiment measures enters the beta conditioning process. For instance, when beta is conditioned on either investor sentiment and default spread (spec B) or on only investor sentiment (spec C), size effect on risk-adjusted returns is explained for all sentiment variables except for PCR. In the case of PCR, the size effect is captured only when it enters the beta conditioning process along with the firm-specific characteristics and default spread (spec D). Furthermore, the value effect is captured when beta is conditioned on firm specific characteristics, default spread, and sentiment (spec D) for EFF, IPOR and PCR.

The impact of the liquidity effect on the risk-adjusted returns is captured for all sentiment variables except for DP and MD when beta is scaled by firm characteristics, default spread, and sentiment (spec D). Interestingly, CEFD is the only sentiment measure that explains liquidity effect for all specifications. Furthermore, we obtain insignificant coefficient estimates on prior returns for all eight sentiment proxies (except DP), suggesting that momentum effect is captured on the risk-adjusted returns of individual stocks. For instance, in the case of put-call ratio for all specifications (except spec A, Ret 4-6), we obtain insignificant estimates for prior returns. Our findings are not consistent with those of Avramov and Chordia (2006), who find that their conditional version of the FF model fails to capture the impact of the momentum effect on risk-adjusted returns. However, they do not include investor sentiment as a conditioning variable in specifying time-varying beta. Our results, therefore, confirm the prominence of investor sentiment in capturing the momentum effect in the conditional FF model.

We also find that the magnitude of the adjusted R^2 for both spec B and C decreases significantly to 2.16% and 2.34%, respectively (in the case of CEFD), relative to 4.06% of the unconditional FF model (see Table 2), thereby indicating the efficacy of the conditional FF models. This is true for all sentiment proxies (for spec B and spec C) except for the IPOV (spec C). However, we observe marginal increase in the adjusted R^2 in the case of specification A and D for all sentiment proxies except for DP. In all, we note the significance of EFF, IPOR and PCR, when included as a conditioning variable, in capturing the impacts of the size, value, liquidity, and momentum effects on risk-adjusted returns of individual stocks.

5.4 Conditional FF model augmented with the Pastor-Stambaugh liquidity factor (FFL)

Pastor and Stambaugh (2003) highlight that stocks with high liquidity betas earn higher average returns than stocks with low liquidity betas. We determine whether the FF model augmented with liquidity factor contributes in capturing size, value, liquidity, and momentum effects on risk-adjusted returns of individual stocks. The results of the FF model augmented with Pastor-Stambaugh's liquidity factor are reported in Table 5. We find that conditioning beta on sentiment (spec C) captures the impact of the size for all sentiment proxies. We observe similar findings for all sentiment measures except for DP when beta is conditioned on sentiment and default spread (spec B). We also find the prominence of the CEFD in capturing value effects on risk-adjusted returns as we obtain insignificant coefficient estimates for all specifications. However, both CEFD and DP fail to capture the turnover effect on risk-adjusted returns when included as a conditioning variable in the asset pricing specification. Our finding differs from that of Ho and Hung (2009), who find that their Fama-French three-factor model, augmented with Pastor and Stambaugh's (2003) liquidity factor, fails to capture the liquidity effect on risk-adjusted returns. As noted earlier, this difference in finding is likely because they use survey-based sentiment measure in their beta conditioning process. When beta is conditioned on firm-specific characteristics, sentiment, and default spread (spec D), momentum effect is explained for sentiment proxies except for CEFD and DP (see Table 5, Ret 2-3 and Ret 4-6). However, CEFD captures momentum effect in the case of specification C and D (see Ret 2-3).[16]

The adjusted R^2 reduces for all sentiment variables for spec B and C and all specifications in the case of PCR. When liquidity factor is conditioned only on PCR, the adjusted R^2 declines significantly to 2.54% as opposed to the unconditional case (i.e. 4.07%). However, when beta is scaled on firm-specific characteristics and sentiment (spec A) and firm-specific characteristics, default spread, and sentiment (spec D), we observe a marginal increase in the adjusted R^2 for all sentiment proxies except for PCR and DP. In all, we note that the EFF, IPOR, PCR, and MD play a significant role in explaining pricing anomalies when included in the beta conditioning process of the FFL model.

5.5 Conditional FF model augmented with the momentum factor (FFM)

The results of the conditional FFM model are presented in Table 6. We find that when EFF is included as a conditioning variable for all four specifications, it captures the impact

[16] Avramov and Chordia (2006) find that their conditional FFL model fails to capture both liquidity and momentum effects on risk-adjusted returns of individual stocks.

of the size effect on risk-adjusted returns. However, the inclusion of the IPOV and CEFD as conditioning variables do not contribute to explaining size effect as we obtain significant estimates. Conditioning beta on each of the eight sentiment variables except DP along with firm-specific characteristics and default spread (spec D) captures the value effect on risk-adjusted returns. Similarly, spec D captures liquidity effect for all sentiment proxies except CEFD. However, when beta is conditioned by both CEFD and default spread (spec B) or by only CEFD (spec C), we obtain insignificant coefficient estimates for turnover. Furthermore, neither CEFD nor DP, when included as a conditioning variable in all specifications, play any significant role in capturing momentum effect on risk-adjusted returns. However, put-call ratio is the only sentiment variable that captures the impact of past three, six, and twelve-month returns on the cross-section of returns. For all other sentiment variables, conditioning beta on firm-specific characteristics, default spread, and sentiment (spec D) explains the predictive power of cumulative past returns.

We obtain lower adjusted R^2 for all sentiment variables for spec B and C, the finding being similar to the conditional versions of the CAPM, FF, and FFL models. We find a marginal increase in the adjusted R^2 for spec A and D for all sentiment proxies (except DP), suggesting a slight improvement in the conditional version of these two specifications. Most of the market anomalies appear to be captured by this model .

5.6 Conditional FF model augmented with the liquidity and momentum factor (FFLM)

Finally, we add the Pastor and Stambaugh (2003) liquidity factor and momentum factor to the Fama-French three-factor model (FFLM) to determine whether it captures the impact of size, value, liquidity, and momentum effects on risk-adjusted returns. The FFLM is the most comprehensive model in our study, and it should capture most of the anomalies for the sentiment measures that failed capture in the earlier models. The results of the conditional FFLM model are reported in Table 7.

We find that the size effect is effectively captured for all sentiment proxies (except for DP and IPOV). For instance, EFF, CEFD, PCR, and MD play a significant role in capturing the size effect for all specifications. Furthermore, conditioning beta on firm-specific characteristics, default spread, and sentiment (spec D) captures the impact of value effect for all sentiment proxies except EFF. For EFF, value effect is effectively explained by spec A and C. Similarly, the impact of liquidity effect on risk-adjusted returns is effectively captured by all sentiment proxies. Interestingly, PCR continues to play a significant role here. Its inclusion as a conditioning variable explains past two-three month returns, the finding similar to the FF and FFM model. Furthermore, the beta spec D (Ret 2-3) captures momentum effect for all sentiment measures (except CEFD and DP). In the case of both CEFD and DP, we obtain significant coefficient estimates for all asset pricing specification. These findings are similar to all the previous models studied except that of the conditional CAPM.[17] This could be due to all sentiment proxies with the exception of DP and CEFD directly deriving from a market-based measures that represent the collective behaviour of all investors. In the case of CEFD and DP, their values are arrived at after considering both the accounting and market-based measures. For instance, the discount on closed-end funds is calculated as a difference between fund NAV and market price, whereas DP considers both the book-value as well as market value of dividend and non-dividend paying firms. A similar observation was also noted in the conditional versions of the FFL and FFM model. However, it would be too premature to claim the above conclusively.

The adjusted R^2 declines marginally for specifications B and C for all sentiment proxies. A similar finding is observed across previous models, suggesting that models where both sentiment and default spread (spec B) and only sentiment (spec C) are included as a conditioning variable successfully capture anomalies in most of the cases with relatively lower adjusted R^2. Furthermore, the inclusion of firm-specific characteristics along with default spread and sentiment (spec D) contributes to capturing the impact of all anomalies in most cases; however, the adjusted R^2 increases marginally relative to unconditional models.

6 Conclusion

In summary, we determine whether incorporating investor sentiment, as conditioning information, can help to capture the predictive ability of size, book-to-market ratio, turnover, and cumulative past returns in explaining the risk-adjusted returns of individual stocks. In assessing the predictive ability of these pricing attributes, we study the conditional case of the single factor CAPM, Fama-French three-factor (FF) model, FF model incorporated with Pastor and Stambaugh's liquidity factor, FF model incorporated with momentum factor, and FF model incorporated with liquidity and momentum factor. We find sentiment augmented conditional models outperform unconditional models in capturing the impacts of size, value, liquidity, and momentum effects on the risk-adjusted returns of individual stocks.

Specifically, we observe that conditioning beta on default spread and either CEFD or dividend premium in the case of CAPM explains predictive power of equity characteristics.

[17]The conditional CAPM successfully captures the impact of all the market anomalies when dividend premium along with default spread (spec B) are included in the beta conditioning process.

The inclusion of EFF, IPOR, and PCR as conditioning variable along with firm-specific characteristics and default spread contributes to capturing pricing anomalies in the case of FF, FFL, FFM, and FFLM models. Furthermore, the significance of the sentiment index in capturing market anomalies is displayed in the conditional versions of both the FFM and FFLM models. In all, our findings indicate that the conditional role of investor sentiment should not be ignored in explaining pricing anomalies as they certainly play a significant role in augmenting the performance of the asset pricing models.

References

[1] Antoniou, C., Doukas, J., and Subrahmanyam, A., 2016. Investor sentiment, Beta, and the Cost of equity capital. Management Science 62. 347-367.

[2] Avramov, D., and Chordia, T., 2006. Asset Pricing Models and financial markets anomalies. Review of financial studies 19. 1001-1040.

[3] Baker, M., and Wurgler, J., 2004. A Catering theory of Dividends. Journal of Finance 59. 1125-1166.

[4] Baker, M., and Wurgler, J., 2006. Investor Sentiment and the Cross-Section of Stock Returns. Journal of Finance 61. 1645-1680.

[5] Baker, M., and Wurgler, J., and Yuan, Y., 2012. Global, Local, and Contagious Investor Sentiment, Journal of Financial Economics 104. 272287.

[6] Ball, R., 1978. Anomalies in relationships between securities' yields yield-surrogates. Journal of Financial Economics 6. 103-126.

[7] Banz, R., 1981. The relationship between returns and market value of common stocks. Journal of Financial Economics 9. 3-18.

[8] Barberis, N., Shleifer, A., and Vishny, R., 1998. A model of investor sentiment. Journal of Financial Economics 49. 307-343.

[9] Basu, S., 1977. Investment performance of cormnon stocks in relation to their price earnings ratios: A test of the efficient market hypothesis. Journal of Finance 32. 663-682.

[10] Bathia, D., and Bredin, D., 2013. An examination of investor sentiment effect on G7 stock market returns. European Journal of Finance 19. 909-937.

[11] Bhandari, L., 1988. Debt-Equity ratio and expected common stock returns: Empirical evidence. Journal of Finance 43. 507-528.

[12] Black, F., 1986. Noise. Journal of Finance 41. 529-543.

[13] Brown, G., and Cliff, M., 2004. Investor Sentiment and the near term stock market. Journal of Empirical Finance 11. 1-27.

[14] Brown, S., Goetzmann, W., Hiraki, T., Shiraishi, N., and Watanabe, N., 2003. Investor Sentiment in Japanese and US Daily Mutual Fund Flows. Working Paper. NBER 9470.

[15] Chan, K., and Chen, N., 1988. An unconditional asset pricing test and the role of firm size as an instrument variable for risk. Journal of Finance 43. 309-325.

[16] Chen, N., Kan, R., and Miller, M., 1993. Are the discounts on closed-end funds a sentiment index?. Journal of Finance 58. 795-800.

[17] Davis, J., 1994, The cross-section of stock returns and survivorship bias: Evidence from delisted stocks. Quarterly Review of Economics and Finance 36. 365-375.

[18] De Bondt, W., and Thaler, R., 1985. Does the stock market overreact?. Journal of Finance 40. 793-805.

[19] DeBondt, W., and Thaler, R. H., 1987. Further evidence on investor overreaction and stock market seasonality. Journal of Finance 42. 557-581

[20] De Long, J.B., Shleifer, A., Summers, L. and Waldmann, R., 1990. Noise Trader Risk in Financial Markets. Journal of Political Economy 98. 703-738.

[21] Easley, D., O'Hara, M., and Srinivas, P., 1998. Option volume and stock prices: Evidence on where informed traders trade. Journal of Finance 53. 431-465.

[22] Fama, E., and French, K., 1992. The cross-section of expected stock returns. Journal of Finance 47. 427-465.

[23] Fama, E., and French, K., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33. 3-56.

[24] Fama, E., and French, K., 1996. Multi factor explanations of asset pricing anomalies. Journal of Finance 51. 55-84.

[25] Fama, E., and French, K., 2015. A five-factor asset pricing model. Journal of Financial Economics 116. 1-22.

[26] Fama, E., and Macbeth, J., 1973. Risk, Return and Equilibrium: Empirical Tests. Journal of Political Economy 81. 609-636.

[27] Ferson, W., Kandel, S., and Stambaugh, R., 1987. Test of asset pricing with time varying expected risk premiums and market betas. Journal of Finance 42. 201-220.

[28] Ferson, W., and Harvey, C., 1991. The variation of economic risk premiums. Journal of Political Economy 99. 385-415.

[29] Ferson, W., and Harvey, C., 1999. Conditioning variables and the cross-section of stock returns. Journal of Finance 54. 1325-1360.

[30] Fisher K., and Statman, M.. 2000. Investor sentiment and stock returns. Financial Analysts Journal 56. 1623.

[31] Frazzini, A., and Lamont, O., 2006. 'Dumb Money: Mutual Fund Flows and the Cross Section of Stock Returns. Journal of Financial Economics 88. 299-322.

[32] Grundy, B., and Martin, S., 2001. Understanding the nature of the risks and source of the rewards to momentum investing. Review of Financial Studies 14. 29-78.

[33] Ho, C., and Hung, C., 2009. Investor Sentiment as conditioning information in asset pricing. Journal of Banking and Finance 33. 892-903.

[34] Ibottson, R., Ritter, J., 1995. Initial public offerings. North-Holland Handbooks of Operations Research and Management Science: Finance. North-Holland, Amsterdam. 993-1016.

[35] Indro, D., 2004. Does Mutual Fund Flow Reflect Investor Sentiment?. Journal of Behavioural Finance 5. 105-115.

[36] Jagannathan, R., and Wang, Z., 1996. The conditional CAPM and the cross-section of expected returns. Journal of Finance 51. 3-53.

[37] Jagannathan, R., and Wang, Z., 1998. An asymptotic theory for estimating beta-pricing models using cross-sectional regression. Journal of Finance 53. 12851309.

[38] Jegadeesh, N., and Titman, S., 1993. Returns to buying winners and selling losers:Implications for stock market efficiency. Journal of Finance 48. 65-91.

[39] Jegadeesh, N., and Titman, S., 2001. Profitability of momentum strategies: An evaluation of alternative explanations. Journal of Finance 56. 699-720.

[40] Kothari, S., Shanken, J., and Sloan, R., 1995. Another Look at the Cross-section of Expected Stock Returns. Journal of Finance 50. 185-224.

[41] Lee, C., Shleifer, A., and Thaler, R., 1991. Investor Sentiment and the Closed End Puzzle. Journal of Finance 46. 75-109.

[42] Lettau, M., and Ludvigson, S., 2001. Resurrecting the (C)CAPM: A cross-sectional test when risk premia are time varying. Journal of Political Economy. 109. 1238-1287.

[43] Lewellen, J., 1999. The time-series relations among expected return, risk, and book-to-market. Journal of Financial Economics 54. 543

[44] Lewellen, J., and Nagel, S., 2006. The conditional CAPM does not explain asset-pricing anomalies Journal of Financial Economics 82. 289-314.

[45] Lewellen, J., Nagel, S., and Shanken, J., 2008. A skeptical appraisal of asset pricing tests. Journal of Financial Economics 96. 175-194.

[46] Li, G., 2007. Time-varying risk aversion and asset prices. Journal of Banking and Finance 31. 243-257.

[47] Lintner, J., 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. Review of Economics and Statistics 47. 13-37.

[48] Litzenberger, R. and Ramaswamy, K., 1979. The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence. Journal of Financial Economics 7. 163-195.

[49] Pan, J., and Poteshman, A., 2006. The Information in Option Volume for Future Stock Prices. Review of Financial Studies 19. 871-908.

[50] Pastor, L., and Stambaugh, R., 2003. Liquidity risks and expected stock returns. Journal of Political Economy 111. 642-685.

[51] Ritter, J., 1991. The Long-Run Performance of Initial Public Offerings, Journal of Finance 46. 3-27.

[52] Rosenberg, B., Reid, K., and Lanstein, R., 1985. Persuasive evidence of market inefficiency. Journal of Portfolio Management 11. 9-17.

[53] Schmeling, M., 2009. Investor sentiment and stock returns: Some international evidence. Journal of Empirical Finance 16. 394-408.

[54] Shanken, J., 1992. On the estimation of beta-pricing models. Review of Financial Studies 5. 1-33.

[55] Sharpe, W., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. Journal of Finance 19. 425-442.

[56] Stambaugh, R., Yu, J., and Yuan, Y., 2012. The short of it: Investor sentiment and anomalies. Journal of Financial Economics 104. 288-302.

[57] Wang, K., 2003. Asset Pricing with Conditioning Information: A New Test. Journal of Finance 58. 161-196.

[58] Warther, V., 1995. Aggregate mutual fund flows and security returns. Journal of Financial Economics 39. 209-235.

[59] Weiss, K., 1989. The post-offering price performance of closed-end funds. Financial Management 18. 57-57.

Table 1: Summary Statistics (3567 firms for the period Jan 1980 to Dec 2014)

	Mean	Std Dev	Coefficient (%)	T-statistics
Excess Returns (%)	0.82	1.99		
Size ($ billion)	2.18	8.31	-0.11	-3.02
B/M	0.75	0.43	0.07	2.23
T/O	0.09	0.08	-0.02	-1.94
Ret 2-3	1.69	3.32	0.59	1.73
Ret 4-6	2.45	4.78	0.74	2.71
Ret 7-12	4.98	10.22	0.46	2.26
Adj R^2 (%)	3.97			

The above table presents the time-series averages of cross-sectional means and standard deviations for 3567 NYSE-AMEX common stocks for the period January 1980 to December 2014. The fourth and fifth column labeled 'coefficient' and 'T-statistics' respectively represents Fama-Mcbeth coefficients and t-values derived from running regression of excess returns on the firm characteristics of size, book-to-market ratio, turnover as well as cumulative returns. Adj R^2 is the average of the adjusted R-square from running the cross-sectional OLS regression. SIZE represents market capitalization, the product of share price and shares outstanding, measured in billion of dollars. B/M represents book-to market ratio of equity. T/O is share turnover, which is monthly trading volume divided by shares outstanding. Ret 2-3, Ret 4-6, and Ret 7-12 are the cumulative returns over the second through third, fourth to sixth and seventh to twelfth months before the current month respectively. A common stock must meet following criteria in order to be included in the analysis: a) the returns data for the current month t and previous 36 months should be available from the CRSP. b) Sufficient data on stock price and common shares outstanding should be available so as to compute SIZE, which is measured by the market capitalization. c) Sufficient data on t-2 trading volume should be available so as to compute TURNOVER, which is measured by the ratio of trading volume to the number of common shares outstanding. d) Sufficient data should be available from COMPUSTAT for computing book-to-market (B/M) ratio as of December of previous calendar year. The value of B/M for July of year t to June of year t+1 is computed using accounting data at the end of calendar year t-1. The B/M ratio greater that 0.995 fractile or less than 0.005 fractile is set as 0.995 and 0.005 respectively. The firms with negative B/M is dropped from our analysis.

Table 2: Unconditional Case (CAPM, FF, FFL, FFM and FFLM)

	CAPM	FF	FFL	FFM	FFLM
SIZE	-0.07	-0.06	-0.06	-0.07	-0.07
fmb	-2.39	-2.12	-2.09	-2.43	-2.39
shk	-2.31	-2.06	-2.03	-2.35	-2.32
jw	-2.47	-2.17	-2.14	-2.51	-2.47
B/M	0.14	0.12	0.12	0.12	0.11
fmb	4.06	3.61	3.53	3.43	3.40
shk	3.71	3.32	3.26	3.17	3.15
jw	4.46	3.92	3.83	3.71	3.68
T/O	-0.02	-0.02	-0.02	-0.02	-0.02
fmb	-2.82	-2.42	-2.45	-1.97	-2.00
shk	-2.64	-2.29	-2.31	-1.88	-1.91
jw	-3.01	-2.56	-2.59	-2.06	-2.10
RET 2-3	1.39	1.34	1.34	1.29	1.29
fmb	4.06	3.91	3.93	3.76	3.78
shk	3.70	3.58	3.60	3.46	3.47
jw	4.45	4.28	4.30	4.10	4.12
RET 4-6	1.49	1.44	1.44	1.40	1.41
fmb	5.47	5.30	5.32	5.16	5.18
shk	4.85	4.72	4.73	4.60	4.62
jw	6.17	5.96	5.98	5.78	5.80
RET 7-12	1.13	1.08	1.08	1.05	1.05
fmb	5.58	5.38	5.38	5.23	5.22
shk	4.94	4.78	4.78	4.66	4.65
jw	6.30	6.06	6.05	5.87	5.86
Adj R^2	4.11	4.06	4.07	4.04	4.04

The above table presents the averages of the coefficient estimates derived from running the second pass cross-sectional OLS regression for the NYSE-AMEX common stocks over 420 months from January 1980 through December 2014. The dependent variable is the excess risk adjusted return using excess market return as the risk factor for the CAPM, excess market returns, SMB,and HML as risk factors for the FF, fama french three factors augmented with Pastor Stambaugh liquidity factor as risk factors for the FFL, fama fremch three factors augmented with momentum factor as risk factors for the FFM and fama fremch three factors augmented with Pastor Stambaugh liquidity factor and momentum factor as risk factors for the FFLM. The independent variables are SIZE, B/M, T/O, RET 2-3, RET 4-6 and RET 7-12 as defined in the methodology section. Values against 'fmb', 'shk' and 'jw' are Fama-Macbeth t-values, Shanken (1992) and Jagannathan and Wang (1998) corrected t-values respectively. Adj R^2 is the average of the adjusted R-square from running the second pass cross-sectional OLS regression. All coefficients are multiplied by 100.

Table 3: Fama-Macbeth estimates with excess market return as the risk factor (CAPM)

	SIZE				B/M				T/O				RET 2-3				RET 4-6				RET 7-12			
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
EFF	0.07	-0.02	-0.02	0.07	-0.03	0.14	0.14	-0.08	-0.03	-0.02	-0.01	-0.02	0.96	1.24	1.20	1.14	1.29	1.41	1.41	1.06	1.11	1.19	1.16	1.23
fmb	2.12	-0.48	-0.51	1.69	-2.11	4.32	4.39	-2.23	-3.42	-2.29	-2.15	-2.36	2.43	3.70	3.61	2.54	3.78	5.32	5.32	2.95	5.40	6.19	6.04	5.68
shk	2.02	-0.47	-0.51	1.62	-2.01	3.92	3.98	-2.11	-3.17	-2.17	-2.05	-2.23	2.29	3.40	3.33	2.39	3.47	4.73	4.73	2.75	4.79	5.41	5.30	5.02
jw	2.23	-0.49	-0.52	1.76	-2.22	4.77	4.85	-2.35	-3.70	-2.41	-2.27	-2.49	2.57	4.03	3.92	2.69	4.12	5.99	5.99	3.16	6.08	7.08	6.88	6.43
Adj R^2	4.29	3.91	3.89	4.36																				
IPOR	0.00	-0.06	-0.06	0.02	-0.04	0.13	0.13	-0.02	-0.02	-0.02	-0.02	-0.03	1.53	1.54	1.52	1.51	1.59	1.64	1.62	1.51	1.03	1.18	1.16	1.03
fmb	0.25	-1.63	-1.70	1.22	-1.43	3.92	3.77	-0.88	-2.90	-3.04	-3.04	-3.25	4.59	4.79	4.72	4.41	6.11	6.50	6.43	5.63	5.21	6.19	6.10	5.20
shk	0.24	-1.57	-1.63	1.18	-1.39	3.59	3.46	-0.86	-2.71	-2.83	-2.83	-3.01	4.14	4.31	4.25	3.99	5.35	5.65	5.60	4.98	4.65	5.42	5.34	4.64
jw	0.25	-1.70	-1.77	1.25	-1.48	4.29	4.11	-0.90	-3.10	-3.26	-3.26	-3.50	5.08	5.33	5.25	4.86	6.97	7.47	7.39	6.37	5.85	7.08	6.96	5.83
Adj R^2	4.15	4.18	4.14	4.35																				
IPOV	0.05	-0.07	-0.07	0.05	-0.04	0.14	0.13	-0.01	-0.03	-0.02	-0.02	-0.03	1.08	1.42	1.38	1.12	1.42	1.54	1.51	1.40	1.01	1.17	1.15	1.03
fmb	2.36	-1.79	-1.79	3.25	-1.24	4.04	3.87	-0.29	-3.56	-2.91	-2.98	-3.88	2.98	4.16	4.05	3.06	4.77	5.68	5.57	4.73	5.00	5.93	5.81	4.91
shk	2.23	-1.71	-1.72	3.01	-1.20	3.69	3.55	-0.29	-3.28	-2.72	-2.78	-3.55	2.78	3.79	3.69	2.85	4.29	5.02	4.93	4.26	4.48	5.21	5.12	4.41
jw	2.49	-1.86	-1.87	3.50	-1.28	4.42	4.23	-0.29	-3.86	-3.12	-3.19	-4.23	3.19	4.57	4.43	3.28	5.31	6.43	6.30	5.26	5.59	6.74	6.60	5.48
Adj R^2	4.38	4.18	4.18	4.41																				
CEFD	0.01	0.03	-0.08	0.01	-0.23	-0.26	0.13	-0.23	-0.01	0.02	-0.02	-0.01	0.37	3.35	1.36	0.42	2.31	1.23	1.42	2.37	1.18	2.04	0.93	1.25
fmb	0.10	0.18	-2.10	0.10	-2.31	-0.93	4.12	-2.31	-0.59	0.60	-2.47	-0.61	0.33	1.81	4.19	0.37	2.70	1.07	5.40	2.77	1.86	2.48	5.00	1.96
shk	0.09	0.18	-2.00	0.10	-2.19	-0.91	3.75	-2.19	-0.58	0.59	-2.33	-0.60	0.33	1.73	3.81	0.37	2.53	1.05	4.79	2.60	1.78	2.34	4.47	1.87
jw	0.10	0.18	-2.21	0.10	-2.44	-0.95	4.52	-2.44	-0.60	0.61	-2.62	-0.62	0.33	1.89	4.61	0.38	2.87	1.10	6.08	2.96	1.94	2.63	5.58	2.05
Adj R^2	4.46	2.45	4.05	4.46																				
PCR	0.06	-0.16	-0.12	0.06	0.05	0.01	-0.04	0.01	0.05	0.14	0.01	0.01	-0.19	0.30	0.88	0.30	0.69	0.69	1.11	0.65	0.68	0.37	0.80	0.60
fmb	2.42	-5.10	-4.02	2.78	2.26	0.15	-1.33	0.27	4.79	7.85	1.55	1.86	-0.38	0.61	2.69	0.76	1.82	1.75	4.14	2.35	2.54	1.27	4.17	2.95
shk	2.28	-4.56	-3.67	2.60	2.14	0.15	-1.29	0.26	4.31	6.66	1.49	1.78	-0.38	0.60	2.53	0.75	1.74	1.68	3.77	2.22	2.39	1.23	3.80	2.76
jw	2.56	-5.71	-4.40	2.96	2.38	0.15	-1.38	0.27	5.33	9.25	1.61	1.94	-0.39	0.62	2.87	0.78	1.90	1.82	4.55	2.48	2.69	1.31	4.58	3.16
Adj R^2	3.82	2.73	2.58	3.89																				
DP	0.07	-0.07	-0.08	0.07	0.01	-0.02	0.12	0.01	-0.03	-0.01	-0.02	-0.03	0.56	2.03	1.34	0.86	0.87	1.00	1.42	1.11	0.48	0.52	0.91	0.61
fmb	2.27	-1.26	-2.28	2.27	2.62	-0.20	3.75	2.64	-3.83	-0.96	-2.39	-3.61	1.26	3.53	4.15	2.13	2.41	2.12	5.41	3.32	1.98	1.46	4.90	2.68
shk	2.15	-1.22	-2.16	2.15	2.46	-0.20	3.44	2.49	-3.51	-0.94	-2.26	-3.33	1.23	3.26	3.78	2.03	2.28	2.01	4.80	3.08	1.89	1.41	4.39	2.52
jw	2.40	-1.29	-2.40	2.40	2.78	-0.20	4.09	2.81	-4.17	-0.99	-2.53	-3.93	1.30	3.83	4.56	2.24	2.55	2.23	6.09	3.59	2.07	1.51	5.46	2.85
Adj R^2	4.40	3.06	3.86	4.40																				
MD	0.03	-0.07	-0.07	0.04	0.00	0.14	0.14	-0.04	-0.02	-0.02	-0.02	-0.02	1.11	1.42	1.40	1.16	1.28	1.51	1.49	1.15	1.04	1.15	1.13	1.06
fmb	1.62	-1.88	-1.85	1.90	-0.34	4.26	4.17	-1.36	-2.68	-2.85	-2.82	-2.64	2.88	4.16	4.07	2.91	4.21	5.57	5.50	3.56	4.99	5.70	5.59	4.99
shk	1.56	-1.79	-1.77	1.82	-0.34	3.87	3.80	-1.31	-2.52	-2.66	-2.64	-2.48	2.69	3.79	3.72	2.72	3.83	4.93	4.87	3.29	4.46	5.03	4.94	4.46
jw	1.68	-1.96	-1.93	1.99	-0.34	4.69	4.58	-1.40	-2.85	-3.04	-3.01	-2.81	3.08	4.57	4.47	3.11	4.63	6.29	6.20	3.87	5.57	6.46	6.32	5.57
Adj R^2	4.24	4.11	4.10	4.39																				
IND	0.04	-0.07	-0.07	0.04	-0.05	0.14	0.14	0.00	-0.03	-0.02	-0.02	-0.03	0.90	1.42	1.39	1.28	1.29	1.52	1.49	1.41	0.97	1.14	1.13	1.05
fmb	1.30	-1.77	-1.74	3.09	-1.04	4.13	4.03	0.06	-3.37	-2.83	-2.85	-3.76	2.26	4.13	4.06	3.47	4.02	5.60	5.47	4.69	4.32	5.64	5.57	4.78
shk	1.26	-1.70	-1.67	2.88	-1.01	3.76	3.68	0.06	-3.12	-2.65	-2.67	-3.45	2.14	3.77	3.70	3.21	3.67	4.95	4.85	4.22	3.92	4.98	4.93	4.29
jw	1.34	-1.85	-1.82	3.32	-1.07	4.54	4.41	0.06	-3.65	-3.02	-3.05	-4.09	2.38	4.54	4.45	3.76	4.40	6.33	6.17	5.21	4.77	6.37	6.29	5.31
Adj R^2	4.35	4.11	4.11	4.43																				

The above table presents the averages of the coefficient estimates derived from running the second pass cross-sectional OLS regression for the NYSE-AMEX common stocks over 420 months from January 1980 through December 2014. The dependent variable is the excess risk adjusted return using excess market return as the risk factor. The independent variables are SIZE, B/M, T/O, RET 2-3, RET 4-6 and RET 7-12 as defined in the methodology section. A, B, C and D denotes four different conditional specifications, as also discussed in the methodology section. The conditional variables considered in the study are different sentiment measures, firm characteristics (SIZE and B/M) and default spread. The sentiment measures include equity fund flow (EFF), IPO first day returns (IPOR), IPO volume (IPOV), closed-end fund discount (CEFD), equity put-call ratio (PCR), dividend premium (DP), change in margin debt (MD) and sentiment index (IND) constructed using the principal component analysis. Values against 'fmb', 'shk' and 'jw' are Fama-Macbeth t-values, Shanken (1992) and Jagannathan and Wang (1998) corrected t-values respectively. Adj R^2 is the average of the adjusted R-square from running the second pass cross-sectional OLS regression. All coefficients are multiplied by 100.

Table 4: Fama-Macbeth estimates with the Fama-French three factors (FF)

	SIZE				B/M				T/O				RET 2-3				RET 4-6				RET 7-12			
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
EFF	-0.05	-0.03	-0.03	-0.01	-0.12	0.18	0.11	-0.22	-0.06	-0.02	-0.01	-0.12	2.60	1.22	1.14	2.30	2.21	1.35	1.33	0.73	1.04	1.16	1.11	-0.32
fmb	-0.43	-0.75	-0.74	-0.04	-2.69	5.36	3.67	-0.53	-1.95	-2.28	-1.86	-1.57	2.53	3.56	3.44	0.90	3.07	5.03	5.03	0.36	2.77	5.88	5.76	-0.29
shk	-0.42	-0.73	-0.73	-0.04	-2.52	4.76	3.38	-0.52	-1.86	-2.16	-1.78	-1.51	2.39	3.28	3.18	0.88	2.86	4.50	4.50	0.36	2.60	5.17	5.08	-0.29
jw	-0.43	-0.76	-0.76	-0.04	-2.86	6.03	3.99	-0.54	-2.04	-2.40	-1.94	-1.63	2.69	3.87	3.72	0.92	3.30	5.62	5.62	0.37	2.95	6.68	6.53	-0.29
Adj R^2	4.45	3.66	3.73	4.49																				
IPOR	0.05	-0.06	-0.06	0.08	-0.13	0.10	0.11	-0.08	-0.03	-0.02	-0.02	-0.02	1.04	1.50	1.49	1.69	1.67	1.58	1.59	0.77	1.15	1.12	1.13	1.63
fmb	1.08	-1.62	-1.71	0.59	-0.65	2.96	3.41	-0.48	-2.69	-2.39	-2.54	-0.96	2.42	4.65	4.66	2.06	5.49	6.22	6.27	1.23	3.26	5.94	5.97	3.35
shk	1.05	-1.56	-1.65	0.58	-0.64	2.77	3.16	-0.47	-2.53	-2.26	-2.39	-0.94	2.28	4.19	4.20	1.96	4.86	5.44	5.48	1.20	3.03	5.22	5.24	3.10
jw	1.11	-1.69	-1.79	0.60	-0.66	3.17	3.69	-0.48	-2.86	-2.53	-2.69	-0.98	2.56	5.16	5.17	2.16	6.19	7.11	7.18	1.27	3.52	6.76	6.80	3.62
Adj R^2	4.38	3.99	4.02	4.54																				
IPOV	0.38	-0.07	-0.07	0.41	-0.69	0.12	0.12	-1.01	-0.02	-0.01	-0.02	-0.01	0.84	1.38	1.32	1.00	1.45	1.49	1.46	1.94	1.37	1.06	1.09	1.39
fmb	4.51	-2.01	-1.81	4.25	-4.16	3.57	3.43	-2.90	-1.26	-1.93	-2.50	-0.37	1.27	4.05	3.89	1.11	2.04	5.50	5.38	2.08	2.85	5.40	5.52	2.08
shk	4.08	-1.92	-1.73	3.86	-3.78	3.29	3.17	-2.71	-1.22	-1.84	-2.36	-0.37	1.23	3.69	3.56	1.08	1.94	4.88	4.78	1.98	2.67	4.79	4.89	1.98
jw	4.99	-2.11	-1.88	4.68	-4.56	3.87	3.71	-3.10	-1.30	-2.02	-2.65	-0.37	1.31	4.43	4.24	1.14	2.14	6.21	6.06	2.19	3.05	6.08	6.23	2.19
Adj R^2	4.52	3.97	4.10	4.54																				
CEFD	0.14	0.00	0.00	0.14	-0.23	0.00	0.01	-0.23	-0.01	-0.03	-0.03	-0.01	0.65	1.85	1.85	0.56	1.65	1.60	1.61	1.55	1.07	0.78	0.80	0.94
fmb	3.65	-0.01	0.05	3.64	-2.98	0.04	0.13	-2.98	-1.40	-1.22	-1.21	-1.56	1.33	2.46	2.46	1.15	4.27	2.56	2.57	4.02	3.94	2.28	2.35	3.45
shk	3.36	-0.01	0.05	3.35	-2.78	0.04	0.13	-2.78	-1.36	-1.19	-1.18	-1.51	1.29	2.32	2.32	1.12	3.87	2.41	2.42	3.67	3.60	2.16	2.23	3.19
jw	3.97	-0.01	0.05	3.96	-3.19	0.04	0.13	-3.19	-1.45	-1.26	-1.25	-1.62	1.37	2.60	2.60	1.18	4.70	2.72	2.73	4.40	4.30	2.40	2.49	3.74
Adj R^2	4.43	2.16	2.34	4.43																				
PCR	0.12	-0.13	-0.13	0.31	-0.18	0.24	0.21	0.18	-0.01	0.04	0.05	-0.03	-0.35	0.16	0.18	-2.62	0.87	0.43	0.43	-0.74	0.48	0.12	0.13	0.34
fmb	2.56	-3.71	-3.87	1.86	-2.09	3.88	3.52	0.53	-0.65	5.24	5.75	-1.34	-0.65	0.35	0.41	-1.34	2.26	1.16	1.16	-0.76	1.66	0.47	0.51	0.57
shk	2.41	-3.41	-3.54	1.78	-1.99	3.55	3.25	0.52	-0.64	4.67	5.07	-1.30	-0.64	0.35	0.40	-1.30	2.14	1.13	1.13	-0.75	1.60	0.46	0.51	0.56
jw	2.72	-4.04	-4.23	1.94	-2.20	4.24	3.82	0.54	-0.66	5.88	6.51	-1.38	-0.66	0.35	0.41	-1.38	2.39	1.19	1.19	-0.77	1.73	0.47	0.52	0.57
Adj R^2	4.00	2.57	2.55	4.05																				
DP	0.01	-0.05	-0.06	0.01	0.00	0.11	0.09	0.00	-0.02	-0.02	-0.02	-0.02	1.31	1.36	1.28	1.26	1.39	1.49	1.42	1.37	0.90	1.00	0.93	0.90
fmb	1.63	-1.31	-1.56	1.64	3.30	3.21	2.77	2.52	-2.32	-2.42	-2.40	-2.40	4.01	4.20	3.95	3.82	5.20	5.60	5.34	5.14	4.86	5.42	5.07	4.84
shk	1.56	-1.27	-1.50	1.58	3.06	2.98	2.59	2.37	-2.20	-2.28	-2.27	-2.27	3.66	3.82	3.61	3.50	4.64	4.96	4.75	4.59	4.36	4.81	4.53	4.35
jw	1.69	-1.35	-1.62	1.70	3.56	3.46	2.95	2.67	-2.45	-2.56	-2.54	-2.54	4.39	4.61	4.32	4.16	5.83	6.34	6.00	5.76	5.42	6.10	5.67	5.39
Adj R^2	3.78	3.55	3.55	3.77																				
MD	0.06	-0.06	-0.06	0.12	-0.06	0.12	0.12	-0.28	-0.02	-0.02	-0.02	-0.03	0.88	1.29	1.34	0.94	1.36	1.47	1.45	0.32	0.97	1.10	1.08	0.97
fmb	2.71	-1.52	-1.49	1.63	-0.75	3.36	3.70	-2.60	-2.34	-2.55	-2.58	-2.74	2.07	3.74	3.93	1.06	4.06	5.38	5.34	0.49	4.24	5.32	5.38	2.74
shk	2.55	-1.46	-1.43	1.56	-0.74	3.11	3.40	-2.45	-2.21	-2.40	-2.43	-2.57	1.97	3.43	3.59	1.03	3.71	4.78	4.75	0.48	3.86	4.73	4.78	2.57
jw	2.89	-1.57	-1.54	1.69	-0.77	3.63	4.02	-2.76	-2.47	-2.70	-2.74	-2.92	2.17	4.07	4.29	1.08	4.45	6.06	6.01	0.49	4.67	5.98	6.05	2.92
Adj R^2	4.52	4.03	4.06	4.55																				
IND	0.08	-0.06	-0.06	0.33	-0.41	0.12	0.12	-0.88	-0.02	-0.02	-0.02	-0.02	0.52	1.38	1.36	2.10	1.65	1.49	1.45	2.15	1.17	1.08	1.09	1.94
fmb	1.81	-1.61	-1.53	2.76	-3.77	3.64	3.64	-2.85	-1.74	-2.27	-2.42	-0.97	1.12	4.04	3.96	2.22	4.22	5.49	5.35	2.12	3.93	5.33	5.37	2.73
shk	1.74	-1.55	-1.48	2.59	-3.46	3.35	3.35	-2.66	-1.67	-2.15	-2.29	-0.95	1.09	3.69	3.62	2.11	3.84	4.87	4.75	2.02	3.60	4.74	4.77	2.56
jw	1.89	-1.67	-1.59	2.94	-4.11	3.95	3.96	-3.04	-1.81	-2.39	-2.57	-1.00	1.15	4.43	4.33	2.34	4.64	6.20	6.02	2.23	4.30	5.99	6.04	2.91
Adj R^2	4.54	4.02	4.06	4.56																				

The above table presents the averages of the coefficient estimates derived from running the second pass cross-sectional OLS regression for the NYSE-AMEX common stocks over 420 months from January 1980 through December 2014. The dependent variable is the excess risk adjusted return using excess market return as the risk factor. The independent variables are SIZE, B/M, T/O, RET 2-3, RET 4-6 and RET 7-12 as defined in the methodology section. A, B, C and D denotes four different conditional specifications, as also discussed in the methodology section. The conditional variables considered in the study are different sentiment measures, firm characteristics (SIZE and B/M) and default spread. The sentiment measures include equity fund flow (EFF), IPO first day returns (IPOR), IPO volume (IPOV), closed-end fund discount (CEFD), equity put-call ratio (PCR), dividend premium (DP), change in margin debt (MD) and sentiment index (IND) constructed using the principal component analysis. Values against 'fmb', 'shk' and 'jw' are Fama-Macbeth t-values, Shanken (1992) and Jagannathan and Wang (1998) corrected t-values respectively. Adj R^2 is the average of the adjusted R-square from running the second pass cross-sectional OLS regression. All coefficients are multiplied by 100.

Table 5: Fama-Macbeth estimates with the Fama-French risk factors augmented with Liquidity Factor (FFL)

	SIZE				B/M				T/O				RET 2-3				RET 4-6				RET 7-12			
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
EFF	-0.03	0.01	-0.03	0.12	-0.15	0.12	0.14	-0.19	-0.04	-0.02	-0.01	-0.06	1.49	1.34	1.16	-1.17	2.05	1.44	1.37	0.52	1.17	1.20	1.12	1.08
fmb	-0.29	0.29	-0.76	0.62	-2.11	3.72	4.50	-0.40	-1.74	-2.66	-1.58	-2.16	1.66	3.89	3.50	-0.39	2.33	5.19	5.15	0.33	2.80	6.05	5.81	1.54
shk	-0.29	0.29	-0.74	0.61	-2.00	3.42	4.07	-0.39	-1.67	-2.50	-1.52	-2.05	1.59	3.56	3.23	-0.39	2.20	4.63	4.60	0.33	2.62	5.31	5.12	1.49
jw	-0.29	0.30	-0.77	0.63	-2.21	4.05	4.98	-0.40	-1.81	-2.83	-1.64	-2.27	1.73	4.25	3.79	-0.40	2.46	5.82	5.77	0.33	2.99	6.90	6.59	1.60
Adj R^2	4.45	3.65	3.75	4.49																				
IPOR	0.04	-0.06	-0.06	0.35	-0.12	0.08	0.11	-0.15	-0.03	-0.02	-0.02	-0.03	1.32	1.54	1.49	-0.57	1.88	1.60	1.59	0.60	0.46	1.13	1.13	1.88
fmb	0.45	-1.60	-1.68	1.52	-0.51	2.53	3.18	-0.50	-2.14	-2.30	-2.61	-0.99	2.11	4.75	4.65	-0.36	4.64	6.32	6.28	0.53	0.93	5.92	5.96	2.51
shk	0.45	-1.54	-1.61	1.47	-0.51	2.38	2.95	-0.49	-2.03	-2.18	-2.45	-0.96	2.01	4.27	4.19	-0.35	4.18	5.51	5.48	0.52	0.91	5.21	5.23	2.37
jw	0.46	-1.66	-1.75	1.58	-0.52	2.68	3.42	-0.51	-2.25	-2.43	-2.77	-1.01	2.22	5.28	5.16	-0.36	5.14	7.24	7.19	0.53	0.95	6.74	6.78	2.66
Adj R^2	4.50	4.02	4.03	4.56																				
IPOV	0.30	-0.07	-0.07	0.51	-0.76	0.12	0.12	-1.36	-0.03	-0.02	-0.02	0.00	0.56	1.37	1.33	-1.91	1.41	1.48	1.45	2.47	1.34	1.06	1.09	1.26
fmb	3.36	-2.05	-1.81	2.76	-3.69	3.60	3.44	-2.54	-1.47	-2.08	-2.54	-0.06	0.73	4.03	3.90	-0.77	1.87	5.43	5.32	1.67	2.65	5.38	5.50	1.29
shk	3.11	-1.95	-1.74	2.59	-3.39	3.32	3.18	-2.39	-1.42	-1.98	-2.39	-0.06	0.71	3.68	3.57	-0.75	1.79	4.82	4.73	1.61	2.49	4.78	4.88	1.25
jw	3.63	-2.15	-1.89	2.94	-4.01	3.91	3.72	-2.69	-1.52	-2.19	-2.69	-0.06	0.74	4.42	4.26	-0.78	1.95	6.12	5.98	1.74	2.82	6.05	6.21	1.33
Adj R^2	4.54	3.99	4.10	4.55																				
CEFD	0.00	0.02	0.02	0.00	-0.01	0.05	0.05	-0.01	-0.02	-0.04	-0.04	-0.03	1.39	0.78	0.82	1.50	1.30	1.57	1.58	1.35	0.79	1.18	1.16	0.91
fmb	-0.13	0.53	0.44	-0.10	-0.77	1.06	1.18	-0.67	-2.75	-3.42	-3.38	-3.60	3.85	1.80	1.90	4.07	4.52	4.59	4.64	4.57	4.02	5.10	5.07	4.59
shk	-0.13	0.52	0.44	-0.10	-0.75	1.03	1.15	-0.66	-2.58	-3.16	-3.13	-3.31	3.53	1.72	1.81	3.71	4.08	4.14	4.19	4.12	3.67	4.55	4.53	4.14
jw	-0.13	0.53	0.45	-0.10	-0.78	1.08	1.22	-0.68	-2.93	-3.70	-3.66	-3.90	4.21	1.88	1.99	4.46	5.00	5.09	5.15	5.06	4.41	5.70	5.67	5.09
Adj R^2	4.28	2.92	3.10	4.27																				
PCR	0.12	-0.05	-0.05	0.20	-0.45	-0.05	-0.03	-0.06	0.01	0.00	0.00	0.00	-0.21	0.70	0.71	-1.80	0.96	0.97	0.95	0.07	0.52	0.62	0.63	0.35
fmb	2.16	-1.69	-1.67	1.10	-1.84	-2.08	-1.15	-0.11	0.59	0.11	0.03	0.06	-0.33	2.37	2.48	-0.73	1.91	4.06	4.03	0.06	0.92	3.75	3.84	0.39
shk	2.05	-1.63	-1.60	1.07	-1.76	-1.98	-1.12	-0.11	0.58	0.11	0.03	0.06	-0.32	2.24	2.34	-0.72	1.82	3.71	3.68	0.06	0.90	3.44	3.52	0.39
jw	2.27	-1.76	-1.74	1.13	-1.92	-2.18	-1.18	-0.11	0.60	0.11	0.03	0.06	-0.33	2.50	2.63	-0.75	1.99	4.45	4.41	0.06	0.94	4.08	4.19	0.40
Adj R^2	4.02	2.58	2.54	4.05																				
DP	0.01	-0.08	-0.07	0.01	0.00	0.08	0.08	0.00	-0.02	-0.02	-0.02	-0.02	1.22	1.14	1.24	1.29	1.34	1.27	1.37	1.39	0.86	0.77	0.90	0.94
fmb	2.18	-2.27	-1.93	2.20	3.47	2.54	2.47	5.16	-2.22	-2.28	-2.19	-2.24	3.73	3.51	3.82	3.87	5.02	4.80	5.21	5.11	4.64	4.13	4.87	5.01
shk	2.07	-2.15	-1.84	2.09	3.21	2.39	2.33	4.60	-2.10	-2.16	-2.08	-2.12	3.43	3.24	3.50	3.55	4.49	4.31	4.64	4.56	4.18	3.76	4.37	4.48
jw	2.29	-2.39	-2.02	2.32	3.76	2.69	2.62	5.78	-2.33	-2.40	-2.31	-2.36	4.06	3.80	4.17	4.23	5.61	5.34	5.84	5.72	5.15	4.53	5.43	5.60
Adj R^2	3.70	3.76	3.68	3.68																				
MD	0.01	-0.06	-0.05	0.18	-0.10	0.11	0.12	-0.14	-0.02	-0.02	-0.02	-0.04	1.56	1.38	1.35	1.10	1.63	1.53	1.46	0.36	1.19	1.12	1.08	1.42
fmb	0.21	-1.49	-1.41	1.46	-0.94	3.34	3.61	-0.79	-1.95	-2.48	-2.58	-2.91	2.46	4.02	3.95	0.75	4.00	5.57	5.39	0.49	4.16	5.44	5.39	3.05
shk	0.21	-1.44	-1.36	1.41	-0.92	3.09	3.33	-0.77	-1.86	-2.34	-2.43	-2.72	2.32	3.67	3.61	0.74	3.66	4.93	4.79	0.48	3.79	4.83	4.79	2.84
jw	0.21	-1.55	-1.46	1.51	-0.97	3.60	3.92	-0.80	-2.04	-2.63	-2.74	-3.11	2.61	4.40	4.32	0.76	4.38	6.29	6.07	0.49	4.57	6.13	6.07	3.27
Adj R^2	4.55	4.04	4.06	4.57																				
IND	0.16	-0.06	-0.05	0.52	-0.55	0.12	0.12	-1.48	-0.04	-0.02	-0.02	-0.03	1.10	1.40	1.36	0.93	1.30	1.47	1.45	2.68	1.37	1.09	1.09	2.52
fmb	1.39	-1.51	-1.48	2.52	-3.37	3.60	3.62	-2.50	-1.91	-2.46	-2.43	-0.77	1.34	4.10	3.99	0.33	1.68	5.42	5.33	1.27	2.76	5.38	5.37	1.88
shk	1.34	-1.45	-1.43	2.37	-3.12	3.32	3.34	-2.36	-1.83	-2.33	-2.29	-0.75	1.30	3.74	3.64	0.33	1.61	4.81	4.74	1.23	2.59	4.78	4.77	1.79
jw	1.44	-1.56	-1.53	2.67	-3.64	3.91	3.94	-2.65	-2.00	-2.61	-2.57	-0.78	1.39	4.50	4.36	0.33	1.75	6.11	5.99	1.31	2.95	6.06	6.04	1.96
Adj R^2	4.56	4.01	4.06	4.58																				

The above table presents the averages of the coefficient estimates derived from running the second pass cross-sectional OLS regression for the NYSE-AMEX common stocks over 420 months from January 1980 through December 2014. The dependent variable is the excess risk adjusted return using excess market return as the risk factor. The independent variables are SIZE, B/M, T/O, RET 2-3, RET 4-6 and RET 7-12 as defined in the methodology section. A, B, C and D denotes four different conditional specifications, as also discussed in the methodology section. The conditional variables considered in the study are different sentiment measures, firm characteristics (SIZE and B/M) and default spread. The sentiment measures include equity fund flow (EFF), IPO first day returns (IPOR), IPO volume (IPOV), closed-end fund discount (CEFD), equity put-call ratio (PCR), dividend premium (DP), change in margin debt (MD) and sentiment index (IND) constructed using the principal component analysis. Values against 'fmb', 'shk' and 'jw' are Fama-Macbeth t-values, Shanken (1992) and Jagannathan and Wang (1998) corrected t-values respectively. Adj R^2 is the average of the adjusted R-square from running the second pass cross-sectional OLS regression. All coefficients are multiplied by 100.

Table 6: Fama-Macbeth estimates with the Fama-French risk factors augmented with Momentum Factor (FFM)

	SIZE				B/M				T/O				RET 2-3				RET 4-6				RET 7-12			
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
EFF	0.01	-0.03	-0.04	-0.34	-0.18	0.10	0.07	-0.54	-0.06	-0.02	-0.01	-0.06	2.21	1.20	1.07	5.87	2.67	1.30	1.29	3.92	1.21	1.17	1.06	-0.21
fmb	0.10	-0.89	-1.20	-0.78	-3.24	3.23	2.13	-0.94	-1.98	-2.17	-1.38	-0.75	2.18	3.55	3.23	1.71	3.77	4.83	4.85	1.58	3.01	6.08	5.53	-0.12
shk	0.10	-0.87	-1.16	-0.76	-3.00	3.00	2.03	-0.92	-1.89	-2.07	-1.33	-0.73	2.07	3.28	3.00	1.65	3.46	4.34	4.35	1.53	2.81	5.33	4.90	-0.12
jw	0.10	-0.91	-1.23	-0.79	-3.49	3.48	2.24	-0.96	-2.07	-2.29	-1.42	-0.76	2.30	3.85	3.48	1.79	4.10	5.38	5.40	1.65	3.23	6.94	6.24	-0.12
Adj R^2	4.48	3.52	3.59	4.49																				
IPOR	0.28	-0.07	-0.08	0.33	-0.08	0.10	0.11	0.10	-0.08	-0.02	-0.02	-0.10	0.07	1.47	1.43	-1.16	1.70	1.55	1.52	0.69	1.70	1.09	1.07	3.68
fmb	1.60	-1.85	-2.14	1.31	-0.38	3.01	3.20	0.16	-3.12	-2.17	-2.16	-1.95	0.10	4.51	4.43	-0.67	2.14	6.09	6.00	0.32	2.66	5.80	5.68	1.89
shk	1.54	-1.77	-2.03	1.27	-0.38	2.81	2.97	0.16	-2.90	-2.06	-2.05	-1.86	0.10	4.08	4.01	-0.66	2.04	5.34	5.26	0.32	2.50	5.11	5.02	1.81
jw	1.66	-1.93	-2.25	1.35	-0.38	3.23	3.44	0.16	-3.35	-2.28	-2.27	-2.04	0.10	4.99	4.90	-0.68	2.25	6.95	6.83	0.32	2.83	6.58	6.43	1.98
Adj R^2	4.52	3.88	3.91	4.55																				
IPOV	0.74	-0.09	-0.09	1.04	-1.28	0.12	0.11	-0.60	-0.02	-0.01	-0.02	-0.09	0.42	1.36	1.27	0.86	1.72	1.48	1.43	1.06	1.57	1.07	1.06	2.30
fmb	5.48	-2.32	-2.35	3.31	-3.77	3.45	3.22	-0.81	-0.85	-1.64	-2.10	-1.30	0.39	4.01	3.73	0.31	1.52	5.44	5.27	0.49	2.04	5.40	5.37	1.31
shk	4.86	-2.20	-2.22	3.07	-3.46	3.18	2.99	-0.80	-0.84	-1.58	-1.99	-1.26	0.39	3.66	3.43	0.31	1.46	4.82	4.69	0.48	1.94	4.80	4.77	1.27
jw	6.18	-2.45	-2.48	3.57	-4.10	3.73	3.46	-0.83	-0.87	-1.71	-2.20	-1.35	0.40	4.39	4.06	0.32	1.57	6.13	5.91	0.49	2.14	6.08	6.05	1.35
Adj R^2	4.54	3.90	4.04	4.57																				
CEFD	-0.04	-0.08	-0.08	-0.04	0.01	0.13	0.14	0.01	-0.02	-0.01	-0.01	-0.02	1.59	1.34	1.29	1.67	1.34	1.28	1.22	1.40	0.93	0.83	0.79	1.09
fmb	-3.83	-2.15	-2.11	-3.85	0.98	4.02	4.13	0.88	-2.07	-1.72	-1.61	-2.08	4.72	4.08	3.92	4.71	4.71	4.80	4.59	4.78	4.54	4.31	4.14	5.13
shk	-3.51	-2.04	-2.01	-3.53	0.95	3.67	3.76	0.86	-1.97	-1.65	-1.55	-1.98	4.25	3.72	3.59	4.24	4.24	4.31	4.14	4.30	4.10	3.91	3.77	4.58
jw	-4.18	-2.26	-2.22	-4.21	1.00	4.41	4.53	0.90	-2.18	-1.80	-1.68	-2.19	5.25	4.47	4.29	5.23	5.24	5.34	5.09	5.31	5.03	4.74	4.54	5.75
Adj R^2	4.18	3.61	3.82	4.15																				
PCR	0.21	-0.59	-0.68	0.16	-0.31	0.78	0.74	0.63	0.02	0.01	0.04	0.03	-0.66	0.48	-0.16	0.47	0.74	0.94	0.55	-0.58	0.15	0.30	0.01	0.86
fmb	1.71	-10.79	-11.39	0.73	-1.77	6.76	7.81	0.90	1.10	0.74	3.67	0.76	-0.61	0.70	-0.23	0.27	0.77	1.73	0.99	-0.32	0.19	0.94	0.04	0.83
shk	1.64	-8.71	-9.11	0.71	-1.70	5.85	6.63	0.88	1.07	0.72	3.37	0.75	-0.60	0.69	-0.23	0.27	0.75	1.66	0.97	-0.31	0.19	0.92	0.04	0.81
jw	1.78	-13.37	-14.25	0.74	-1.85	7.81	9.20	0.92	1.13	0.75	3.99	0.78	-0.62	0.71	-0.24	0.27	0.78	1.81	1.02	-0.32	0.19	0.96	0.04	0.84
Adj R^2	4.04	2.63	2.64	4.06																				
DP	0.01	-0.07	-0.10	0.01	0.00	0.12	0.09	0.00	-0.02	-0.02	-0.01	-0.01	1.29	1.34	1.29	1.27	1.34	1.17	1.14	1.38	0.86	0.80	0.79	0.87
fmb	1.62	-1.73	-2.61	1.70	3.58	3.56	2.70	3.11	-2.36	-1.86	-1.48	-1.48	3.94	4.05	3.97	3.78	5.07	4.25	4.17	5.14	4.65	4.02	4.09	4.57
shk	1.55	-1.66	-2.45	1.63	3.30	3.28	2.54	2.90	-2.23	-1.78	-1.43	-1.42	3.60	3.70	3.63	3.47	4.53	3.87	3.80	4.59	4.19	3.67	3.73	4.13
jw	1.68	-1.80	-2.77	1.77	3.89	3.86	2.88	3.35	-2.49	-1.95	-1.53	-1.53	4.31	4.44	4.34	4.12	5.67	4.68	4.59	5.76	5.16	4.40	4.49	5.06
Adj R^2	3.78	3.32	3.61	3.76																				
MD	0.18	-0.06	-0.06	-0.17	-0.11	0.12	0.12	-0.41	-0.02	-0.02	-0.02	0.01	0.55	1.31	1.28	4.26	1.40	1.46	1.41	0.80	0.93	1.09	1.04	1.73
fmb	5.03	-1.55	-1.60	-0.38	-1.81	3.39	3.54	-1.13	-2.29	-2.29	-2.21	0.20	1.36	3.84	3.73	1.51	4.36	5.37	5.19	0.45	4.04	5.33	5.18	1.05
shk	4.50	-1.50	-1.54	-0.38	-1.73	3.14	3.27	-1.10	-2.17	-2.17	-2.10	0.20	1.32	3.52	3.43	1.46	3.95	4.77	4.63	0.45	3.69	4.74	4.62	1.03
jw	5.63	-1.61	-1.66	-0.38	-1.89	3.67	3.84	-1.17	-2.42	-2.42	-2.33	0.20	1.41	4.19	4.06	1.57	4.81	6.04	5.82	0.46	4.43	6.00	5.81	1.08
Adj R^2	4.53	4.02	4.03	4.59																				
IND	0.60	-0.06	-0.07	0.97	-0.83	0.13	0.11	-0.55	-0.04	-0.01	-0.02	-0.07	0.70	1.40	1.31	-0.78	1.54	1.49	1.42	-0.04	1.75	1.06	1.05	1.99
fmb	4.29	-1.72	-1.80	4.36	-3.48	3.67	3.39	-1.56	-1.48	-1.91	-1.97	-1.78	0.68	4.07	3.81	-0.44	1.47	5.48	5.23	-0.02	2.61	5.25	5.21	2.03
shk	3.89	-1.65	-1.73	3.95	-3.22	3.37	3.13	-1.51	-1.42	-1.82	-1.88	-1.71	0.67	3.72	3.49	-0.44	1.42	4.86	4.66	-0.02	2.46	4.68	4.64	1.94
jw	4.72	-1.79	-1.88	4.81	-3.77	3.99	3.66	-1.62	-1.53	-1.99	-2.07	-1.86	0.69	4.47	4.15	-0.45	1.52	6.18	5.86	-0.02	2.77	5.90	5.84	2.13
Adj R^2	4.57	4.00	4.03	4.58																				

The above table presents the averages of the coefficient estimates derived from running the second pass cross-sectional OLS regression for the NYSE-AMEX common stocks over 420 months from January 1980 through December 2014. The dependent variable is the excess risk adjusted return using excess market return as the risk factor. The independent variables are SIZE, B/M, T/O, RET 2-3, RET 4-6 and RET 7-12 as defined in the methodology section. A, B, C and D denotes four different conditional specifications, as also discussed in the methodology section. The conditional variables considered in the study are different sentiment measures, firm characteristics (SIZE and B/M) and default spread. The sentiment measures include equity fund flow (EFF), IPO first day returns (IPOR), IPO volume (IPOV), closed-end fund discount (CEFD), equity put-call ratio (PCR), dividend premium (DP), change in margin debt (MD) and sentiment index (IND) constructed using the principal component analysis. Values against 'fmb', 'shk' and 'jw' are Fama-Macbeth t-values, Shanken (1992) and Jagannathan and Wang (1998) corrected t-values respectively. Adj R^2 is the average of the adjusted R-square from running the second pass cross-sectional OLS regression. All coefficients are multiplied by 100.

Table 7: Fama-Macbeth estimates with the Fama-French risk factors augmented with Liquidity factor and Momentum Factor (FFLM)

	SIZE				B/M				T/O				RET 2-3				RET 4-6				RET 7-12			
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
EFF	-0.04	0.01	-0.03	0.31	-0.18	0.09	0.02	2.87	-0.06	-0.01	-0.01	-0.27	2.44	1.43	1.33	7.86	2.56	1.45	1.52	1.50	1.41	1.25	1.29	2.99
fmb	-0.34	0.15	-0.78	0.43	-1.81	2.82	0.61	2.19	-2.25	-1.67	-1.49	-2.35	2.36	4.15	3.91	0.68	4.05	5.19	5.57	0.23	3.45	6.48	6.52	1.00
shk	-0.34	0.15	-0.77	0.42	-1.73	2.64	0.60	2.08	-2.13	-1.60	-1.44	-2.22	2.23	3.78	3.58	0.67	3.69	4.63	4.93	0.23	3.19	5.64	5.67	0.97
jw	-0.35	0.15	-0.80	0.43	-1.89	3.01	0.62	2.31	-2.37	-1.74	-1.55	-2.48	2.49	4.56	4.27	0.69	4.43	5.82	6.29	0.23	3.74	7.45	7.51	1.02
Adj R^2	4.48	3.63	3.74	4.50																				
IPOR	0.20	-0.07	-0.08	-0.71	0.00	0.09	0.10	-1.86	-0.08	-0.02	-0.02	-0.03	1.12	1.52	1.42	17.67	2.40	1.57	1.52	9.00	1.20	1.09	1.07	-0.95
fmb	1.19	-1.86	-2.11	-0.73	0.01	2.62	3.01	-2.05	-3.28	-2.15	-2.25	-0.30	1.16	4.62	4.42	1.50	2.65	6.18	6.00	1.68	1.21	5.77	5.66	-0.35
shk	1.15	-1.78	-2.01	-0.71	0.01	2.46	2.81	-1.95	-3.04	-2.04	-2.14	-0.29	1.12	4.17	4.00	1.45	2.49	5.41	5.27	1.62	1.18	5.09	5.00	-0.35
jw	1.22	-1.95	-2.22	-0.74	0.01	2.78	3.23	-2.15	-3.54	-2.26	-2.38	-0.30	1.19	5.13	4.88	1.55	2.82	7.06	6.84	1.75	1.25	6.54	6.41	-0.35
Adj R^2	4.55	3.88	3.91	4.57																				
IPOV	0.55	-0.09	-0.09	2.00	-1.34	0.12	0.11	-0.23	-0.02	-0.01	-0.02	-0.08	0.22	1.34	1.28	0.16	1.16	1.46	1.41	1.35	1.27	1.06	1.06	4.23
fmb	5.03	-2.36	-2.33	2.66	-4.43	3.44	3.27	-0.16	-0.96	-1.84	-2.13	-0.64	0.24	3.95	3.74	0.03	1.24	5.36	5.19	0.31	2.23	5.36	5.35	1.00
shk	4.50	-2.24	-2.20	2.50	-4.01	3.18	3.04	-0.16	-0.94	-1.76	-2.03	-0.63	0.24	3.61	3.44	0.03	1.20	4.77	4.63	0.31	2.12	4.76	4.76	0.97
jw	5.62	-2.50	-2.46	2.83	-4.89	3.72	3.53	-0.16	-0.98	-1.92	-2.24	-0.65	0.25	4.32	4.08	0.03	1.28	6.04	5.82	0.32	2.35	6.03	6.02	1.02
Adj R^2	4.54	3.93	4.02	4.58																				
CEFD	-0.02	-0.07	-0.06	-0.02	0.00	0.10	0.11	0.00	-0.02	-0.02	-0.02	-0.01	1.46	1.42	1.37	1.51	1.30	1.36	1.31	1.27	0.80	0.93	0.88	0.77
fmb	-2.02	-1.86	-1.77	-2.02	2.17	3.12	3.52	0.84	-2.45	-2.15	-2.07	-1.81	4.28	4.45	4.30	4.28	4.62	5.13	4.96	4.38	4.06	4.92	4.67	3.87
shk	-1.93	-1.78	-1.70	-1.92	2.06	2.90	3.25	0.82	-2.31	-2.05	-1.97	-1.74	3.89	4.03	3.90	3.89	4.17	4.58	4.44	3.97	3.70	4.41	4.21	3.55
jw	-2.12	-1.94	-1.84	-2.12	2.28	3.35	3.81	0.86	-2.59	-2.27	-2.17	-1.89	4.71	4.92	4.74	4.71	5.12	5.74	5.54	4.83	4.45	5.49	5.19	4.23
Adj R^2	4.09	3.71	3.80	4.07																				
PCR	0.17	-0.06	-0.05	3.13	-0.46	-0.02	0.00	-0.98	-0.03	0.00	0.01	0.12	-0.79	0.40	0.33	-11.80	-0.24	0.61	0.56	-23.72	-0.38	0.36	0.35	-3.42
fmb	1.40	-2.06	-1.79	1.77	-2.19	-0.77	0.11	-0.28	-1.23	0.22	1.46	1.01	-0.65	1.30	1.11	-0.54	-0.26	2.45	2.33	-1.24	-0.46	2.08	2.08	-0.47
shk	1.35	-1.96	-1.71	1.69	-2.08	-0.76	0.11	-0.28	-1.19	0.22	1.41	0.98	-0.64	1.26	1.08	-0.53	-0.26	2.32	2.21	-1.20	-0.46	1.98	1.98	-0.47
jw	1.45	-2.16	-1.86	1.84	-2.30	-0.79	0.12	-0.29	-1.26	0.22	1.51	1.03	-0.66	1.34	1.14	-0.54	-0.26	2.60	2.46	-1.27	-0.47	2.18	2.19	-0.48
Adj R^2	4.05	2.47	2.49	4.07																				
DP	0.01	-0.08	-0.08	0.01	0.00	0.10	0.09	0.00	-0.02	-0.02	-0.01	-0.03	1.24	1.32	1.26	1.40	1.34	1.44	1.39	1.41	0.84	0.96	0.93	0.86
fmb	2.15	-2.13	-2.24	2.16	3.00	3.18	2.74	1.19	-2.01	-2.03	-1.83	-3.49	3.73	4.08	3.89	4.18	4.94	5.51	5.29	5.09	4.47	5.21	5.03	4.43
shk	2.04	-2.02	-2.13	2.06	2.80	2.95	2.57	1.16	-1.91	-1.93	-1.75	-3.22	3.43	3.72	3.56	3.80	4.43	4.88	4.71	4.55	4.04	4.64	4.50	4.01
jw	2.26	-2.24	-2.36	2.28	3.21	3.42	2.92	1.23	-2.10	-2.12	-1.91	-3.78	4.06	4.47	4.25	4.59	5.51	6.22	5.94	5.70	4.94	5.84	5.62	4.90
Adj R^2	3.70	3.72	3.73	3.65																				
MD	0.05	-0.05	-0.06	-0.09	-0.25	0.11	0.12	2.15	-0.01	-0.02	-0.02	0.15	1.58	1.35	1.28	-3.85	1.62	1.49	1.42	6.28	1.19	1.07	1.04	7.76
fmb	0.49	-1.35	-1.54	-0.08	-1.94	3.08	3.46	0.81	-1.10	-2.26	-2.20	0.76	1.41	3.92	3.73	-0.32	2.40	5.42	5.23	0.84	2.93	5.25	5.16	1.71
shk	0.48	-1.31	-1.48	-0.08	-1.85	2.87	3.19	0.80	-1.07	-2.14	-2.09	0.74	1.36	3.59	3.43	-0.32	2.27	4.81	4.66	0.82	2.74	4.68	4.61	1.64
jw	0.49	-1.40	-1.59	-0.08	-2.03	3.30	3.74	0.83	-1.12	-2.38	-2.31	0.77	1.45	4.29	4.06	-0.33	2.54	6.10	5.87	0.86	3.14	5.90	5.79	1.78
Adj R^2	4.57	4.04	4.03	4.60																				
IND	0.38	-0.06	-0.06	0.25	-0.87	0.13	0.12	0.72	-0.03	-0.02	-0.02	-0.12	1.02	1.37	1.31	-5.70	1.27	1.42	1.42	0.45	1.66	1.04	1.05	3.72
fmb	3.17	-1.70	-1.75	0.46	-4.08	3.88	3.41	0.72	-1.53	-2.17	-1.98	-1.82	1.12	4.00	3.83	-1.02	1.44	5.22	5.21	0.12	3.18	5.18	5.21	1.64
shk	2.95	-1.63	-1.68	0.46	-3.72	3.55	3.15	0.71	-1.47	-2.06	-1.89	-1.74	1.09	3.65	3.51	-1.00	1.39	4.65	4.64	0.12	2.95	4.62	4.65	1.57
jw	3.42	-1.77	-1.82	0.47	-4.47	4.24	3.69	0.73	-1.59	-2.28	-2.07	-1.90	1.15	4.38	4.18	-1.05	1.49	5.86	5.84	0.13	3.42	5.81	5.85	1.70
Adj R^2	4.57	3.94	4.04	4.60																				

The above table presents the averages of the coefficient estimates derived from running the second pass cross-sectional OLS regression for the NYSE-AMEX common stocks over 420 months from January 1980 through December 2014. The dependent variable is the excess risk adjusted return using excess market return as the risk factor. The independent variables are SIZE, B/M, T/O, RET 2-3, RET 4-6 and RET 7-12 as defined in the methodology section. A, B, C and D denotes four different conditional specifications, as also discussed in the methodology section. The conditional variables considered in the study are different sentiment measures, firm characteristics (SIZE and B/M) and default spread. The sentiment measures include equity fund flow (EFF), IPO first day returns (IPOR), IPO volume (IPOV), closed-end fund discount (CEFD), equity put-call ratio (PCR), dividend premium (DP), change in margin debt (MD) and sentiment index (IND) constructed using the principal component analysis. Values against 'fmb', 'shk' and 'jw' are Fama-Macbeth t-values, Shanken (1992) and Jagannathan and Wang (1998) corrected t-values respectively. Adj R^2 is the average of the adjusted R-square from running the second pass cross-sectional OLS regression. All coefficients are multiplied by 100.